Healthy Cognition in Old Age: Effects of an Engaged Lifestyle and Cognitive Training

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PER LA MIA NONNA

"ANYONE WHO STOPS LEARNING IS OLD, WHETHER AT TWENTY OR EIGHTY."

HENRY FORD

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ABSTRACT

Healthy cognitive functioning is a key aspect of successful aging and a crucial component of the well-being of older adults. On the group level, crystallized abilities (e.g., factual knowledge) remain relatively stable until old age, fluid cognitive abilities (e.g., working memory, reasoning), however, decline gradually across the lifespan. Therefore, and in light of the projected demographic changes, the identification of modifiable lifestyle factors and the development of interventions that promote successful cognitive aging have become increasingly important. Thus, the main question of this thesis was if an engaged lifestyle and cognitive training interventions have a positive impact on cognitive ability, cognitive plasticity, and functional ability in everyday life in older adults.

In the first article of this thesis, the relation between indicators of an engaged lifestyle (i.e., intellectual, social and physical activities) and indicators of functional ability in everyday life (i.e., objective everyday performance and self-reported failures in everyday life) was investigated, while considering cognitive ability (i.e., working memory) as a potential mediator of this association. Using a latent-variables approach, we found that intellectual activities (i.e., game playing) were positively related to objective everyday performance and that physical activities (i.e., sports) were negatively related to self-reported failures in everyday life. Further, the relation between intellectual activities and functional ability in everyday life was found to be fully mediated by working memory performance. Thus, working memory may be one pathway by which an engaged lifestyle is linked to functional ability in everyday life.

In the second article of this thesis, cognitive training studies in older adults were reviewed with regards to the range of training and transfer effects, maintenance effects, and training-related structural and functional brain changes. In sum, cognitive training leads to substantial training gains, but evidence for transfer to untrained tasks and abilities is mixed. It is argued that methodologically sound studies are needed to further investigate the effectiveness of cognitive training. In addition, the role of between-person differences and within-person covariates of cognitive performance should be further examined to facilitate the development of individually tailored interventions. Further, studying transfer effects in real-life settings will enhance the ecological validity of training interventions.

In the third article of this thesis, the effectiveness of a working memory training intervention was investigated with respect to near transfer to untrained working memory tasks, and far transfer to untrained, but related cognitive abilities (i.e., shifting, inhibition, and fluid

intelligence). Therefore, a relatively large sample of older adults was randomly assigned to either a working memory or visual search training group, both receiving 25 sessions of adaptive cognitive training. By using multiple indicators for each cognitive ability and Bayesian linear mixed effects models, we found evidence for substantial training effects on the group level in both training groups. However, the data provided evidence supporting the absence of near transfer to working memory and far transfer to all of the assessed abilities. These results indicate that generalization of working memory training gains is limited and that working memory training is, at the moment, not effective to improve general cognitive functioning in older adults.

Finally, in the fourth article of this thesis, the association between 29 individual differences factors and change in training performance was investigated in three samples of younger and older adults to identify predictors of cognitive training progress. A Latent Growth Curve modeling approach was used to estimate and predict individual differences in the training trajectories. The data provides evidence against individual differences in demographic variables, real-world cognition, motivation, cognition-related beliefs, personality, leisure activities, and computer literacy/training experience predicting change in training performance. Only baseline cognitive performance was related to change in training performance in both samples of younger adults, confirming the magnification account of cognitive change.

ZUSAMMENFASSUNG

Intakte kognitive Fähigkeiten sind ein grundlegender Aspekt des erfolgreichen Alterns und ein wesentlicher Bestandteil des Wohlbefindens älterer Menschen. Auf Gruppenebene zeigt sich, dass kristalline kognitive Fähigkeiten (z.B. Faktenwissen) bis ins hohe Alter relativ stabil bleiben, während fluide kognitive Fähigkeiten (z.B. Arbeitsgedächtnis, logisches Schlussfolgern) sukzessive über die Lebensspanne abnehmen. Deshalb, und in Anbetracht der vorhergesagten demographischen Veränderungen, ist die Identifikation modifizierbarer Lifestyle-Faktoren und die Entwicklung von Interventionen die das erfolgreiche kognitive Altern fördern von grösster Bedeutung. Diese Arbeit geht deshalb der Frage nach, ob ein aktiver Lebensstil und kognitive Trainingsinterventionen einen positiven Effekt auf die kognitiven Fähigkeiten, die kognitive Plastizität und die funktionelle Fähigkeit im Alltag älterer Menschen haben.

Im ersten Teil dieser Arbeit wurde der Zusammenhang zwischen Indikatoren eines aktiven Alltags (d.h. intellektuelle, soziale und physische Aktivitäten) und Indikatoren funktioneller Fähigkeit im Alltag (d.h. objektive Alltagsfähigkeit und selbst-berichtete Probleme im Alltag) untersucht, während kognitive Fähigkeit (d.h. Arbeitsgedächtnis) als potentieller Mediator dieses Zusammenhangs berücksichtigt wurde. Auf dem Level latenter Konstrukte wurde ein positiver Zusammenhang zwischen intellektuellen Aktivitäten (d.h. Spiele spielen) und der objektiven Alltagsfähigkeit, sowie ein negativer Zusammenhang zwischen physischen Aktivitäten (d.h. Sport) und selbst-berichteten Problemen im Alltag gefunden. Des Weiteren wurde der Zusammenhang zwischen intellektuellen Fähigkeiten und funktioneller Fähigkeit im Alltag vollständig durch das Arbeitsgedächtnis mediiert. Dies bedeutet, dass das Arbeitsgedächtnis ein möglicher Mechanismus ist, worüber ein aktiver Alltag mit funktioneller Fähigkeit im Alltag verbunden ist.

Im zweiten Teil dieser Arbeit wurden kognitive Trainingsstudien mit älteren Menschen zusammengefasst und bezüglich Trainings- und Transfereffekten, Aufrechterhaltungseffekten, und trainings-bedingten strukturellen und funktionellen Veränderungen im Gehirn evaluiert. Zusammengefasst zeigt sich, dass kognitives Training zu substantiellen Trainingseffekten führt, aber die Evidenz für Transfereffekte zu untrainierten kognitiven Aufgaben und Fähigkeiten gemischt ist. Es wird argumentiert, dass methodisch fundierte Studien benötigt werden um die Effektivität kognitiver Trainingsinterventionen zu untersuchen. Zusätzlich soll die Rolle von individuellen Unterscheiden und intraindividuellen Kovariaten kognitiver Performanz weiter

untersucht werden, um die Entwicklung individualisierter Trainingsinterventionen zu fördern. Um die ökologische Validität kognitiver Trainings zu erhöhen soll Transfer zukünftig in Settings untersucht werden, die das reale Leben und seine Anforderungen stärker widerspiegeln.

Im dritten Teil dieser Arbeit wurde die Effektivität einer Arbeitsgedächtnis-Intervention im Hinblick auf nahen Transfer zu untrainierten Arbeitsgedächtnis-Aufgaben und fernem Transfer zu untrainierten, aber mit dem Arbeitsgedächtnis zusammenhängenden kognitiven Fähigkeiten (d.h. Shifting, Inhibition und fluide Intelligenz) untersucht. Dafür wurde eine relativ grosse Stichprobe älterer Menschen zufällig entweder einer Arbeitsgedächtnis-Gruppe oder einer Gruppe die die visuelle Suche trainiert, zugeordnet. Beide Gruppen erhielten 25 Sitzungen eines adaptiven kognitiven Trainings. Mittels multiplen Indikatoren und Bayesianischen gemischten linearen Modellen konnte gezeigt werden, dass sich beide Trainingsgruppen substantiell in den trainierten Aufgaben verbesserten. Die Daten liefern jedoch Evidenz für die Absenz von nahem Transfer zu untrainierten Arbeitsgedächtnis-Aufgaben und fernem Transfer zu allen untersuchten Fähigkeiten. Diese Resultate deuten darauf hin, dass die Generalisierbarkeit der Performanzgewinne während des Arbeitsgedächtnis-Trainings limitiert ist und dass Arbeitsgedächtnis-Training im Moment keine wirksame Möglichkeit darstellt, um die generelle kognitive Leistungsfähigkeit im höheren Alter zu verbessern.

Im vierten Teil dieser Arbeit wurde der Zusammenhang zwischen 29 Faktoren und der Performanzveränderung während des kognitiven Trainings in drei Stichproben von jüngeren und älteren Erwachsenen untersucht, um Prädiktoren für den kognitiven Trainingsgewinn zu identifizieren. Mittels latenter Wachstumskurvenmodellen wurden die individuellen Unterschiede in den kognitiven Trainingsverläufen geschätzt und vorhergesagt. Die Daten liefern Evidenz gegen einen prädiktiven Wert von demographischen Variablen, Alltagskognition, Motivation, kognitions-bezogenen Überzeugungen, Persönlichkeit, Alltagsaktivitäten, sowie Computer- und Trainingserfahrung. Nur Baseline-Kognition hängt mit der Performanzveränderung während des Trainings bei jüngeren Erwachsenen zusammen, und bestätigt damit die Magnifikations-Hypothese.

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1 THEORETICAL BACKGROUND

The population's share of adults over the age of 65 has never been higher than today and it is likely to further increase in the upcoming decades. While this demographic trend has major consequences on the societal and economic level by putting high demands on, say, the health-care system or the labor market, it also affects the aging individuals themselves, which face serious challenges when growing older. One of these challenges is related to the deterioration of older adults' cognitive abilities, a process that, on the group level, initiates in adulthood and can accelerate in very old age, depending on the ability of interest (e.g., Hedden & Gabrieli, 2004; Schaie, 1996). Historically, cognitive abilities have been broadly classified into crystallized and fluid abilities (Cattell, 1943; 1963). Whereas the former describes abilities that are well-learned, acquired based on past experience, and assumed to be accumulated across the lifespan (e.g., factual knowledge and vocabulary, see also Kan, Kievit, Dolan, & van der Maas, 2011), the latter is defined as the ability to recognize relationships between pieces of information and dealing with novel information (e.g., reasoning and working memory; WM). These concepts are also being referred to as the pragmatics (i.e., crystallized abilities) and the mechanics (i.e., fluid abilities) of intelligence (Baltes, 1993).

Similarly to human development in general, cognitive development is characterized by multi-directional age-related change trajectories (Baltes, 1987). It has been argued that, on the group level, crystallized abilities remain relatively stable across the lifespan, whilst fluid abilities tend to deteriorate with increasing age (e.g., Horn & Cattell, 1967; Salthouse, 2004; 2006; 2010). In a similar vein, Hedden and Gabrieli (2004) distinguished between three types of cognitive trajectories. First, well-practiced abilities such as vocabulary or semantic knowledge remain relatively stable and tend to rapidly decline after the age of 70. Second, life-long stability is only found for autobiographical memory or emotional processing. Third, basic cognitive functions such as processing speed or WM are assumed to decline gradually from early adulthood into old age. This strict distinction between age-related changes in fluid versus crystallized abilities has recently been challenged by Hartshorne and Germine (2015), who showed a much more heterogeneous and complex pattern of age-related cognitive change trajectories.

Importantly, however, mental health and, more specifically, the ability to engage in stimulating activities and to be mentally active are fundamental components of successful aging (e.g., Lawton et al., 1999; Reichstadt, Depp, Palinkas, & Jeste, 2007). The fact (or the fear) of both age-related cognitive decline and the associated reduction of functional ability in everyday life, that is, the ability to performance tasks that are relevant for everyday life (e.g., Yam & Marsiske, 2013), has sparked research in two major fields of cognitive gerontopsychology: (1) the study of enriching lifestyle factors (e.g., intellectual, physical, and social activities) and their associations with cognitive functioning, and (2) the development and investigation of cognitive training interventions that aim at improving cognitive functioning and promoting successful aging.

While many studies have found a beneficial effect of leisure activities on both cognitive functioning and the prevention of cognitive impairment (see Allan, McMinn, & Daly, 2016; Bherer, Erickson, & Liu-Ambrose, 2013; Hertzog, Kramer, Wilson, & Lindenberger, 2009 for reviews), so far, only few studies have addressed the question of whether engagement in an active lifestyle is linked to functional ability in old age, and if so, what the underlying mechanisms of this relationship are. Therefore, the first central question of this thesis was whether engagement in stimulating leisure activities is related to (a) cognitive functioning and (b) functional ability in everyday life in older adults and whether the association between leisure activities and functional ability in everyday life is mediated through cognitive functioning.

In contrast, numerous cognitive training interventions aiming at stabilizing or improving cognitive abilities or postponing age-related cognitive decline have been developed and investigated in the recent years. By using compelling marketing messages and making persuasive promises, so called “brain-training” companies and their products attract large crowds. The market research company “SharpBrains” estimated that in 2013 the brain-training and -assessment software market had sales of US $715 million and that the sales will increase up to US $3.4 billion by 2020 (see Simons et al., 2016 for a detailed discussion on commercial brain-training). Despite the impressive figures, the evidence for the effectiveness of cognitive training is far from being conclusive (see Au et al., 2015; Dougherty, Hamovitz, & Tidwell, 2016; Karbach & Verhaeghen, 2014; Lampit, Hallock, & Valenzuela, 2014; Melby-Lervåg & Hulme, 2013; Melby-Lervåg, Redick, & Hulme, 2016; Sala & Gobet, 2017; Schwaighofer, Fischer, & Bühner, 2015; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017 for meta-analyses). Severe methodological issues and differences between the study designs make it difficult to draw firm conclusions and to settle the debate regarding the effectiveness of cognitive training. Thus, the second central question of this thesis was whether (a) a cognitive training intervention for older adults is effective with regard to training gains and transfer effects and (b) whether individual differences factors predict training performance.

1.1. Cognitive Enrichment

With the ultimate aim to identify predictors of healthy cognitive aging, a large body of literature has investigated the relationship between an engaged lifestyle and cognitive functioning in older adults. In their conceptual framework, the cognitive enrichment-hypothesis, which incorporates Baltes' propositions of lifespan development (Baltes, 1987), Hertzog et al. (2009) propose that cognitive development is, comparable to human development in general, characterized by gains and losses, with gains becoming less frequent and losses becoming more frequent with increasing age. The conceptual framework highlights that in addition to these ontogenetic changes, substantial within- and between-person variation in the level of cognitive functioning exists and that cognitive ability can be enhanced across the entire lifespan. The authors propose the existence of a lower (or suboptimal) and an upper (or optimal) limit of cognitive plasticity, which are both defined by biological aging processes, including functional and structural changes in the brain (see Raz, 2000 for an overview), and that these lower and upper limits of cognitive plasticity also change as a function of biological age. In their view, the upper limit represents an individuals' maximum cognitive functioning in an optimally enriched environment and the lower limit represents the minimal possible level of cognitive functioning when the environment provides no enrichment at all. Between those two boundaries, they propose, is a range of possible levels of cognitive functioning on which a given individual can operate, and these levels are distributed around the typical developmental average for this age group of cognitive functioning. Whether or not and to what extent individuals deviate from this typical ontogenetic trend in either direction, is a function of both relatively fixed age-related biological processes, modifiable behavioral enrichment activities and the environment in which the individual operates, and denotes the extent of possible positive or negative plasticity (see also Lövdén, Bäckman, Lindenberger, Schaefer, & Schmiedek, 2010).

To achieve positive cognitive plasticity, that is, to improve or stabilize cognitive functioning throughout the lifespan, the cognitive-enrichment hypothesis proposes that engaging in an active lifestyle, which is rich in stimulating activities, is associated with higher levels of cognitive functioning and may prevent age-related or neuropathological cognitive decline (see also Salthouse, 2006 for the mental-exercise hypothesis). Three main activity clusters have repeatedly been suggested and investigated in this context: (1) intellectually stimulating activities, (2) physical activity and (3) social engagement (e.g., Harada, Natelson Love, & Triebel, 2013; Hertzog et al., 2009).

1.1.1. Intellectual Activities

Intellectual enrichment can be conceptually decomposed into two major components: (1) intellectually enriching *life contexts* and (b) intellectually *stimulating activities* (cf. Vemuri et al., 2014). Regarding the first, there is some evidence that early life contexts, such as formal education (e.g., Banks & Mazzonna, 2012, but see Van Dijk, Van Gerven, Van Boxtel, Van der Elst, & Jolles, 2008) or bilingualism (e.g., Bak, Nissan, Allerhand, & Deary, 2014) can be protective against age-related decline in late life. Further, it has been shown that occupational complexity is positively associated with cognitive functioning and negatively with cognitive decline (e.g., Finkel, Andel, Gatz, & Pedersen, 2009; Marquie et al., 2010; Potter, Helms, & Plassman, 2008; Potter, Plassman, Helms, Foster, & Edwards, 2006; Smart, Gow, & Deary, 2014; Then et al., 2015) and that retirement negatively impacts cognitive functioning (e.g., Bonsang, Adam, & Perelman, 2012; Mazzonna & Peracchi, 2012).

The second component involves enrichment that occurs as a consequence of intellectually stimulating activities. It must be noted, however, that it is sometimes difficult to define the term intellectual activities and to conceptually distinguish it from other forms of activities such as social activities, as the participation in most activities involve cognitive processes to some extent (cf. Hertzog et al., 2009) and some activities may therefore involve more than one component (e.g., playing card games or learning a choreography). In general, there is evidence for a positive association of engagement in intellectual activities with level in cognitive functioning and for a negative association with cognitive decline (e.g., Bielak, Hughes, Small, & Dixon, 2007; Bosma et al., 2002; Ghisletta, Lövdén, & Bickel, 2006; Hultsch, Hertzog, Small, & Dixon, 1999; Mitchell et al., 2012; Mueller, Raymond, & Yochim, 2013; Schooler & Mulatu, 2001; Vemuri et al., 2014; Wilson, Segawa, Boyle, & Bennett, 2012; Wilson et al., 2013, but see Aartsen, Smits, van Tilburg, Knipscheer, & Deeg, 2002). In addition, some studies have also reported bi-directional effects of intellectual activities and cognition (Bosma et al., 2002; Small, Dixon, McArdle, & Grimm, 2012; Wilson et al., 2012), indicating that individuals who are cognitively healthier also engage more in intellectually stimulating activities.

1.1.2. Physical Activities

With regard to physical enrichment, research has strongly focussed on the effects of two types of activities on cognitive functioning: (1) aerobic training and (b) resistance/strength training (see Bherer et al., 2013; Mcauley, Mullen, & Hillman, 2013; Voss, Nagamatsu, Liu-

Ambrose, & Kramer, 2011 for reviews). Both cross-sectional studies (e.g., Clarkson-Smith & Hartley, 1989; Renaud, Bherer, & Maquestiaux, 2010) and longitudinal studies (e.g., Barnes, Yaffe, Satariano, & Tager, 2003; Gow, Mortensen, & Avlund, 2012) have reported beneficial effects of objectively measured and self-reported general physical activity on cognitive functioning or cognitive decline. Similarly to the research on intellectual activities, studies have also identified bi-directional effects between cognitive functioning and physical activity (Daly, McMinn, & Allan, 2015; see also Allan et al., 2016), indicating that individuals with low levels of cognitive functioning showed subsequent decreases in physical activity and individuals with high levels of physical activity showed more stable levels of cognitive functioning over time. The strongest evidence for a causal relationship between cognitive functioning and physical activity stems from intervention studies, which showed that participation in a physical activity program leads to substantial improvements in cognitive ability, with the strongest effects found for executive functions (see Colcombe & Kramer, 2003 for a meta-analysis).

A number of neural mechanisms have been proposed to potentially mediate the relationship between physical activity and cognitive function (see Allan et al., 2016; Voss et al., 2011 for details), including (1) an increase in neurotrophins (i.e., proteins that induce development and function of neurons such as the brain-derived neurotrophic factor), (2) changes in brain structure (e.g., neurogenesis), and (3) angiogenesis (i.e., formation of new blood vessels).

1.1.3. Social Activities

Besides intellectual and physical activities, social activities are part of what is being referred to as an engaged lifestyle. In contrast to the former, evidence for a beneficial effect of social activities on cognitive functioning is somewhat more mixed. Some studies found that participation in social activities (e.g., Bourassa, Memel, Woolverton, & Sbarra, 2017; James, Wilson, Barnes, & Bennett, 2011; Windsor, Gerstorf, Pearson, Ryan, & Anstey, 2014) and social support (e.g., Gow, Corley, Starr, & Deary, 2013) is associated with less cognitive decline, others found that loneliness is associated with steeper cognitive decline (e.g., Donovan et al., 2017; Gow et al., 2013; Gow & Mortensen, 2016). However, other longitudinal studies did not find such a consistent association between social activity and cognitive functioning across time (e.g., Aartsen et al., 2002), or did so only cross-sectionally (e.g., Brown et al., 2012; Green, Rebok, & Lyketsos, 2008). Further, some evidence exists for the association between social activity and social support (but not social network size) and cognitive functioning (Krueger et al., 2009). One study found that concurrent cognitive functioning was more strongly associated with social-private activities (e.g., visiting friends) than with social-public activities (e.g., attending club meetings; Jopp & Hertzog, 2010). In a similar vein, Bielak, Mogle, and Sliwinski (2017) found that fluctuations in daily social-private (but not social-public) activities were related to fluctuations daily cognition (i.e., episodic memory) in older adults, strengthening the relative importance of private over public social activities for daily cognitive functioning.

1.2. Cognitive Training

Although both cross-sectional and longitudinal studies provide valuable evidence when investigating associations of leisure activities with cognitive ability, there are some methodological drawbacks. First, cross-sectional studies do not allow conclusions regarding the directionality of the effects: it might be that individuals with higher levels of leisure activity engagement are those who are cognitively fitter, or it might be exactly the other way around. This issue can be solved using longitudinal data and the appropriate statistical approaches (e.g., lead-lag models), however, the possibility of a hidden third-variable (e.g., age, education level) accounting for the associations between leisure activities and cognitive ability can still not be ruled out (cf. Corley, Cox, & Deary, 2017). The most straightforward approach to investigate the *causal effect* of stimulating activities on cognitive functioning are randomised-controlled experimental training studies, in which participants are randomly assigned to either a training or control condition (see e.g., Park et al., 2014; Stine-Morrow, Parisi, Morrow, & Park, 2008 for training studies using leisure activity interventions).

1.2.1. Cognitive Plasticity

The idea behind cognitive training interventions is based on the concept of cognitive plasticity. The term has been defined as the organisms' capability for reactive change in functional capacity in the possible range of cognitive performance, which is driven by a mismatch between the supplies of the organism and the demands in the environment (Lövdén et al., 2010). Both positive (e.g., cognitive training) and negative changes (e.g., neurological deterioration) in functional capacity can cause plastic changes in behaviour and cognitive plasticity and can therefore be seen as an adaptive process (cf. Baltes, Staudinger, & Lindenberger, 1999). In the case of positive cognitive plasticity and cognitive training, it is assumed that the demands in the environment (e.g., the WM requirements of the task) are higher than the available capacity of the individual (e.g., the current WM capacity of an individual).

Lövdén et al. (2010) further argue that in order to maintain plasticity it is important to not just keep the initial demands high (e.g., non-adaptive training interventions), but to constantly keep the mismatch between the demands and the available capacity sufficiently high (e.g., through adaptive algorithms during training).

Most training studies in older adults have focused on the delivery of structured cognitive activities (e.g., cognitive tasks), rooting in the so-called testing-the-limits paradigm originally developed by Baltes and colleagues (e.g., Baltes & Kliegl, 1992; Singer, Lindenberger, & Baltes, 2003). This was shortly followed by many training studies delivering cognitive strategies, such as the Method of Loci, a mnemonic strategy to facilitate the encoding and memorization of serial information. These strategy-based training studies have shown to strongly (and specifically) increase cognitive performance on the trained or highly similar tasks, even in old age (see Verhaeghen, Marcoen, & Goossens, 1992 for a meta-analysis). Interestingly, performance improvements acquired as a consequence of strategy instruction have shown to be maintained over a 5-year interval in the Advanced Cognitive Training for Independent and Vital Elderly (ACTIVE) study (Ball et al., 2002). In contrast, strategy-based training approaches have shown only limited generalization to previously untrained and dissimilar tasks or abilities (e.g., Bailey, Dunlosky, & Hertzog, 2014; Zinke, Zeintl, Eschen, Herzog, & Kliegel, 2012, but see Willis et al., 2006). Given the limited generalization effects, process-based cognitive training interventions have become increasingly popular. Based on the process-overlap theory (Kovavs & Conway, 2016), it has been argued that training-related cognitive improvements should generalize or *transfer* from the trained tasks to untrained tasks or domains if they share the same underlying cognitive processes. The degree to which performance improvements on the trained tasks generalize to other tasks or abilities has been further broken down into *near*, *medium* and *far transfer* based on the conceptual distance between the tasks or abilities (Noack, Lövdén, Schmiedek, & Lindenberger, 2009).

A large number of process-based cognitive training interventions have specifically targeted WM. WM is a hypothetical, capacity-limited cognitive system responsible for simultaneously remember and manipulate pieces of information (e.g., Baddely, 1986; Cowan, 2005) that ultimately serves to perform complex cognitive processes (e.g., Oberauer, 2009). Engle (2002) and Engle, Kane, and Tuholski (1999) conceptualized this capacity as a limited domain-general attentional capacity that assures maintaining task focus or inhibiting irrelevant information. Thus, individual differences in WM capacity are assumed to reflect differences in the domain-general capability to control attention (Feldman Barrett, Tugade, & Engle, 2004).

In general, the effectiveness of WM training in terms of producing near transfer to untrained WM tasks or untrained cognitive abilities such as intelligence is still highly debated across many study populations (i.e., healthy children, younger, and older adults, children with attention deficit hyperactivity disorder, brain injured patients with WM deficits; see Au et al., 2015; Karbach & Verhaeghen, 2014; Melby-Lervåg & Hulme, 2013; Melby-Lervåg et al., 2016; Rapport, Orban, Kofler, & Friedman, 2013; Sala & Gobet, 2017; Schwaighofer et al., 2015; Soveri et al., 2017; Weicker, Villringer, & Thöne-Otto, 2015 for meta-analyses).

1.2.2. Methodological Considerations

Based on these studies, no clear pattern of results has emerged that would answer the question of whether and to what extent training effects generalize to untrained abilities. Two factors impede robust conclusions. On the one hand, a number of study design issues or differences in study designs (e.g., passive vs. active control groups, assessment of skills vs. abilities), which have extensively been discussed in the literature, make it difficult to compare the results between training paradigms (e.g., Guye, Röcke, Mérillat, von Bastian, & Martin, 2016; Noack, Lövdén, & Schmiedek, 2014; Shipstead, Redick, & Engle, 2012; von Bastian, Guye, & De Simoni, in press; von Bastian & Oberauer, 2014).

To gain further insight into which training interventions lead to generalized effects or which populations are especially responsive to cognitive training, researchers made strong efforts to identify possible moderators of training effectiveness, such as the targeted study population (e.g., younger versus older adults), the nature of the study design (e.g., type of control group, length or intensity of the training regime), the type of delivery of the training (e.g., in groups versus individually, supervised versus unsupervised). Some of these factors have shown to moderate training effectiveness. For instance, Sala and Gobet (2017) found that effect sizes of far transfer effects are inversely related to study design quality, that is, studies with a qualitatively optimal design (random allocation procedure and active control groups) produced less far transfer. Another meta-analysis by Schwaighofer et al. (2015) found that longer training sessions and supervised training is more effective. This is partially in line with the meta-analysis by Lampit et al. (2014) who showed that home-based individual training is less effective than in-lab group training. Further, Lampit et al. (2014) found that less intensive interventions (i.e., up to 3 sessions per week) are more effective than more intensive interventions (i.e., more than 3 sessions per week). However, other meta-analyses have not found such moderator effects (e.g., Karbach & Verhaeghen, 2014; Melby-Lervåg et al., 2016). Thus, at the moment, it is still unclear which factors moderate training effectiveness and a meta-analysis of meta-analyses is needed.

On the other hand, limited power due to small study samples and data-analytical issues (e.g., null hypothesis significance testing; NHST) makes it impossible to draw certain conclusions, such as to confirm null effects and thus the ineffectiveness of cognitive training. As argued in von Bastian et al. (in press), we and others (e.g., Dougherty, Hamovitz, & Tidwell, 2016; Sprenger et al., 2013, see also Dienes, 2014) suggested to move from NHST to a Bayesian approach when evaluating the (in-)effectiveness of cognitive training interventions.

When using inferential statistics, we typically differentiate between the null hypothesis (i.e., H_0, e.g., absence of training or transfer effects) and the alternative hypothesis (i.e., H_1, e.g., the presence of training or transfer effects). However, as illustrated by Dienes and Mclatchie (2017), we aim to distinguish between three potential states of evidence: 1) evidence for H_0, 2) evidence for neither H_0 nor H_1, and 3) evidence for H_1 after we collected the data and conducted the statistical analysis. In NHST, only the H_0 is modeled (e.g., no differences in population means) and subsequently, the probability of the data given the H_0 can be calculated. Consequently, the *p*-value only distinguishes between evidence against the H_0 and the first two states of evidence (i.e., evidence for H_0 and evidence for neither H_0 nor H_1), but it cannot distinguish between evidence for H_0 and evidence for neither H_0 nor H_1. This is highly unfortunate for intervention research, when the ineffectiveness of an intervention is of high practical interest too. In contrast, as further illustrated by Dienes and Mclatchie (2017), one outstanding advantage of the Bayesian framework is that more differentiated conclusions can be drawn in this context. In the Bayesian framework, three models are used to calculate the Bayes factor: 1) a model for the H_0, 2) a model for the H_1, and 3) a model for the data. The Bayes factor is a continuous index that provides information about the evidence for one hypothesis (typically the H_1) over another hypothesis (typically the H_0; or vice versa). Thus, a Bayes Factor of 10 for the alternative hypothesis indicates that the data is 10 times more likely given H_1 relative to H_0, and can be interpreted as strong evidence (cf. Wetzels & Wagenmakers, 2012). Conversely, a Bayes factor of 1/10 for the null hypothesis indicates that the data is 10 times less likely given H_0 relative to H_1. If, however, the Bayes factor is around 1, it indicates that the data does not distinguish well between the two hypotheses and that there is not enough evidence for neither the null nor the alternative hypothesis. Thus, the Bayes factor provides information about all of the three potential states of evidence.

1.2.3. Effectiveness of Cognitive Training: Bayesian Evidence

Recently, Dougherty et al. (2016) re-evaluated the meta-analysis of Au et al. (2015) using Bayesian statistics. The meta-analysis included 20 WM training studies applying adaptive single or dual *n*-back paradigms to adults aged 18 to 50 years with the primary interest of evaluating far transfer to fluid intelligence. Whilst the meta-analysis found a small but significant effect of *n*-back training on transfer to fluid intelligence, the conclusion of Dougherty et al. (2016) was somewhat more pessimistic. In their re-evaluation, the concluded that there is indeed some evidence for the alternative hypothesis (i.e., presence of transfer to fluid intelligence) when considering studies using a passive control group. However, when evaluating studies using an active control group, they found moderate evidence for the null hypothesis (i.e., absence of transfer to fluid intelligence), with, however, almost half of the studies providing only insufficient evidence for both hypotheses. It is likely that the small average sample sizes of the control and treatment groups in this meta-analysis (n = 20) have caused or at least contributed to the insufficient sensitivity to provide conclusive evidence.

In a similar vein, we re-evaluated the meta-analysis of Lampit et al. (2014) using the Bayesian approach (von Bastian et al., in press). Unlike the meta-analysis from Au et al. (2015), Lampit et al., (2014) included 52 cognitive training studies that were not restricted to WM paradigms, but cognitive paradigms in general. Further, they focused on studies including healthy older adults with a mean age between 60 and 82 years. We evaluated the included studies and reinterpreted the evidence for and against transfer effects to measures of WM and measures of executive functions/reasoning, and we did so separately for those studies using passive control groups and those using active control groups. Similar to Dougherty et al. (2016) we found that the majority of studies provided only insufficient evidence for either the alternative or the null hypothesis across all the assessed measures. More specifically, we found some evidence for the alternative hypothesis regarding transfer to WM, particularly for those studies with larger sample sizes and active control groups (see Figure 1). When it comes to transfer to executive functions and reasoning our findings largely overlap with those of Dougherty et al. (2016). More specifically, we found that some studies provide evidence for the null hypothesis, particularly so when considering the studies using active control groups. Most studies, however, offer only insufficient evidence for either hypotheses (see Figure 2).

In summary, based on recent Bayesian re-evaluations of some of the meta-analyses in the field (Dougherty et al., 2016; von Bastian et al., in press), it is hardly possible to conclusively settle the debate on the effectiveness of cognitive, or more specifically, WM training in both younger and older adults as most studies provide only ambiguous evidence favoring neither the null nor the alternative hypothesis.

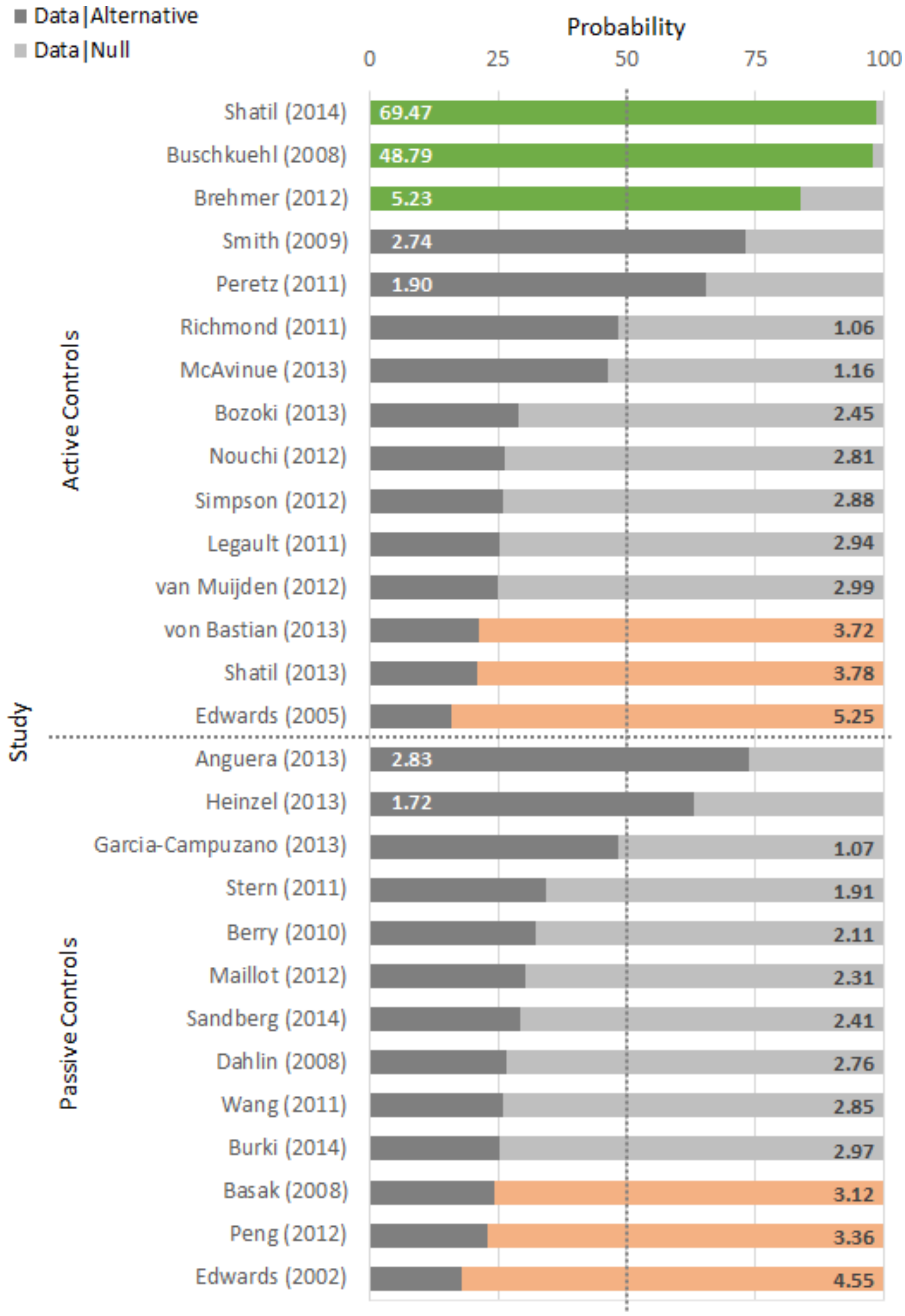

Figure 1. Bayes factors for transfer effects to working memory for the studies included in Lampit et al. (2014). Bayes factors in favor of the alternative hypothesis are depicted on the left and colored in green if greater than 3 and for the null hypothesis on the right and colored in orange if greater than 3. From “How strong is the evidence for the effectiveness of working memory training?” by C. C. von Bastian, S. Guye, and C. De Simoni (in press), in M. F. Bunting, J. M. Novick, M. R. Dougherty, and R. W. Engle (Eds), *Cognitive and Working Memory Training: Perspectives from Psychology, Neuroscience, and Human Development*, New York, NY: Oxford University Press.

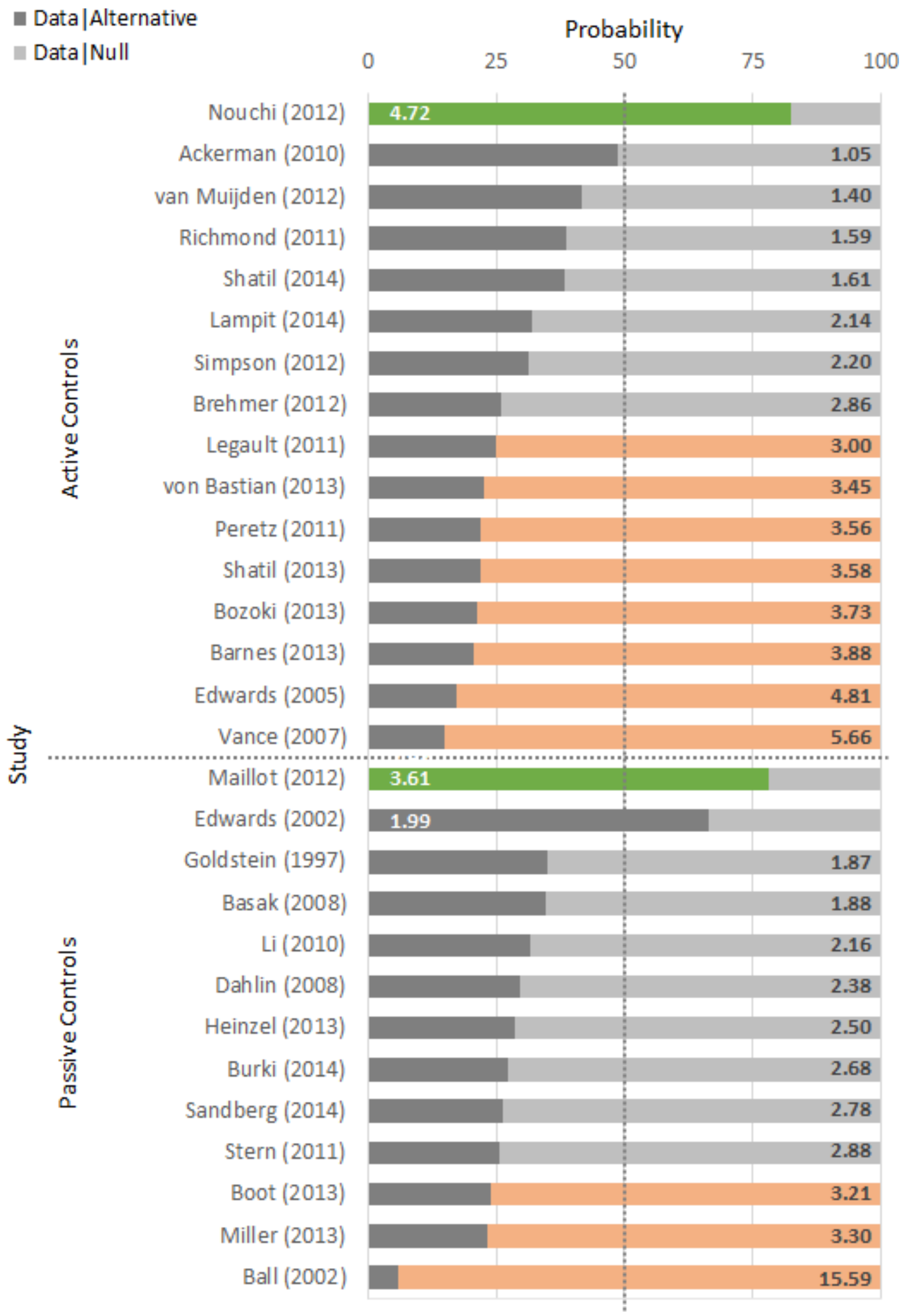

Figure 2. Bayes factors for transfer effects to executive functions and reasoning for the studies included in Lampit et al. (2014). Bayes factors in favor of the alternative hypothesis are depicted on the left and colored in green if greater than 3 and for the null hypothesis on the right and colored in orange if greater than 3. From "How strong is the evidence for the effectiveness of working memory training?" by C. C. von Bastian, S. Guye, and C. De Simoni (in press), in M. F. Bunting, J. M. Novick, M. R. Dougherty, and R. W. Engle (Eds), *Cognitive and Working Memory Training: Perspectives from Psychology, Neuroscience, and Human Development*, New York, NY: Oxford University Press.

2 OUR APPROACH AND MAIN OBJECTIVES

The general objective of this thesis was to investigate factors that positively influence cognitive ability, cognitive plasticity and functional ability in everyday life in old age. To approach these objectives, the Healthy Cognitive Aging and Plasticity (h-CAP) project was conducted (see Figure 3).

2.1. THE HEALTHY COGNITIVE AGING AND PLASTICITY STUDY

The main goal of the h-CAP project was to evaluate the range of transfer after a WM training intervention in older adults and to identify individual differences that might predict training effectiveness. Thus, a number of study-design (e.g., Chapter 4; Article II - *Plasticity in different age groups: Adult lifespan*) and data-analytical issues (e.g., von Bastian et al., in press) that have frequently been voiced in the cognitive training literature have been addressed in this project. Further, we included a variety of between-person variables to investigate their associations with cognitive ability and functional ability in everyday life. Finally, to contribute to enhance transparency and reproducibility in science, data and analyses scripts used for the publications resulting from the h-CAP project are publicly available on the Open Science Framework (OSF).

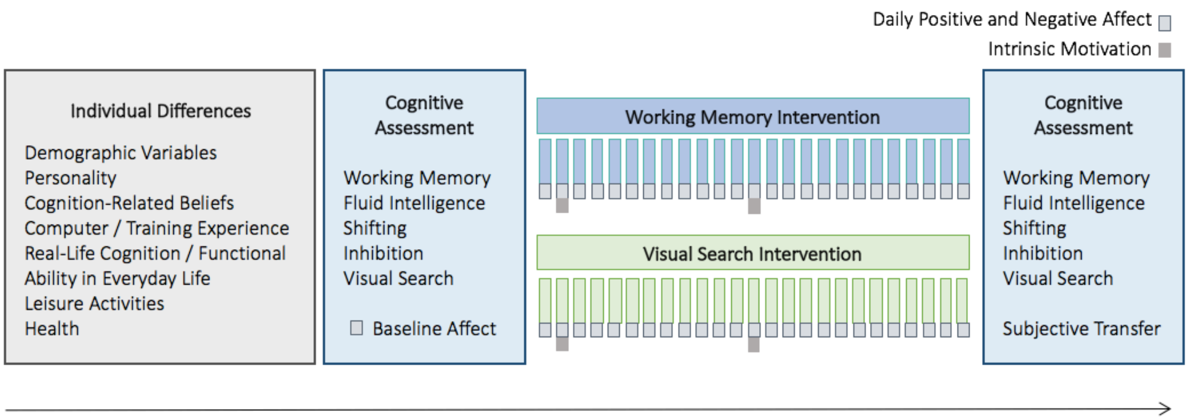

Figure 3. Overview of the Healthy Cognitive Aging and Plasticity project.

2.1.1. ADDRESSING STUDY DESIGN AND DATA-ANALYTICAL ISSUES

In order to settle the debate on the effectiveness of cognitive training interventions, well-powered and methodologically sound studies are needed. The h-CAP project is a randomized-controlled, double-blind training intervention study using a relatively large number of older adults ($N = 142$ - 158, depending on the study phase). An active and adaptive control group was used to control for potential expectancy effects. Further, multiple cognitive indicators were used for each cognitive transfer ability, to model potential performance improvements on the level of abilities. In addition, wherever possible, data was analysed using Bayesian statistics.

2.1.2. TARGETING WORKING MEMORY

Choosing WM as the primary target for the cognitive training intervention had two main reasons: First, age-related differences in WM have frequently been reported, with younger adults outperforming older adults (e.g., Dobbs & Rule, 1989). Thus, the question if and to what extend WM itself can be enhanced through cognitive training in old age has important implications for the well-being of older adults, as cognitive health is regarded as one of the most important indicators of well-being in old age (e.g., Lawton et al., 1999). Second, measures of WM capacity have shown not only to be associated with lab-based measures of cognitive ability, such as intelligence (see Ackerman & Lohman, 2006; Conway, Kane, & Engle, 2003 for overviews), but also real-life cognitive activities such as language or reading comprehension (see Feldman Barrett et al., 2004 for an overview). Thus, it is hypothesized that WM improvements would translate into performance increases in related cognitive abilities and cognitive activities, if the intervention successfully targets those processes that are shared between WM and the related abilities or activities.

2.1.3. INDIVIDUAL DIFFERENCES

It is likely that cognitive training interventions are not equally effective for all individuals. Thus, it has been argued that individual differences such as personality or motivation may moderate training effectiveness (see Katz, Jones, Shah, Buschkuehl, & Jaeggi, 2016 for an overview). However, most training studies suffer from uncomfortably small sample sizes that prevent the investigation of such moderator effects. Some research has been conducted on age and baseline cognitive performance as moderators of training and transfer effects. Regarding the former, most studies report that younger adults benefit more from training than older adults (e.g., Schmiedek, Lövdén, & Lindenberger, 2010; von Bastian, Langer, Jäncke, & Oberauer, 2013), but some studies report the opposite pattern (e.g., Bherer et al., 2008). In a similar vein, some studies showed that individuals with lower baseline cognitive performance benefit more from training (e.g., Zinke et al., 2012; 2014), whereas other studies reported that individuals with initially higher cognitive performance gain more from training (e.g., Bürki, Ludwig, Chicherio, & de Ribaupierre, 2014). Also, there is evidence for personality traits (i.e., neuroticism and conscientiousness) moderating both training and transfer effects (e.g., Studer-Luethi, Bauer, & Perrig, 2016; Studer-Luethi, Jaeggi, Buschkuehl, & Perrig, 2012). Given the ambiguous evidence regarding some of these factors and the under-investigation of other relevant individual differences factors such as motivation (but see Brose, Schmiedek, Lövdén, & Lindenberger, 2012) or previous training and computer experience, we included a large number of individual differences factors (i.e., demographic variables, real-world cognition, motivation, cognition-related beliefs, personality, leisure activities, and computer literacy/training experience) to investigate potential moderator effects in three relatively large samples of younger and older adults.

2.1.4. Moving Towards Open Science

Generating reproducible knowledge is one of the core principles in science. In recent years, non-reproducible research results have caused much scepticism towards scientific study design and analysis practices and the resulting implications, both among researchers and the general public alike. In their seminal work, the Open Science Collaboration led by Brian Nosek conducted replications of 100 studies published in well-known psychology journals (i.e., the reproducibility project; Open Science Collaboration, 2015). They found that whilst out of the original studies 97% reported significant results, the same was the case for only 36% of the replications, with strength of original evidence being the most predictive factor of replication success. These findings and the resulting heated discussions in the field highlight not only the strong need for replication studies (which currently are not encouraged enough by journal editors and reviewers), but also for more transparent science practices in general that improve reproducibility and verifiability of the generated study results.

One possibility to improve transparency is to make data and analytical procedures freely available to fellow researchers (or to anyone), so that other scientists can re-evaluate or replicate a study more easily. For the h-CAP project, the OSF was used, which is a free and open source platform to support researchers during the entire research lifecycle. Among other functions, it allows to upload data, code and study protocols which can be shared and made publicly available to the community. All the data and analyses scripts of the publications resulting from the h-CAP project are available on the OSF (or will be made available upon acceptance of the manuscript in preparation).

2.2. MAIN OBJECTIVES

The first research objective was to investigate the association of leisure activities with cognitive ability and functional ability in everyday life. More specifically, we investigated the association between an engaged lifestyle (i.e., intellectual, social and physical activities) and functional ability in everyday life, while considering cognitive ability (i.e., WM) as a potential mediator of this association (see Chapter 3; Article I – *Functional ability in everyday life: Associations with an engaged lifestyle are mediated by working memory*). The remaining three research objectives aim at understanding the scope of cognitive plasticity following cognitive training and identifying potential moderators of cognitive plasticity. More specifically, the first step was to critically review the current literature on cognitive training interventions in older adults (see Chapter 4; Article II – *Plasticity in different age groups: Adult lifespan*). Following this literature review, the third objective was to evaluate the effectiveness of a WM training intervention in terms of training and transfer effects in older adults using Bayesian statistics (see Chapter 5; Article III – *Working memory training in older adults: Bayesian evidence supporting the absence of transfer*). Finally, the fourth objective was to identify potential moderators of cognitive plasticity in both younger and older adults (see Chapter 6; Article IV – *Do individual differences predict change in training performance: A latent growth curve modeling approach*). An overview on the main objectives is presented in Figure 3.

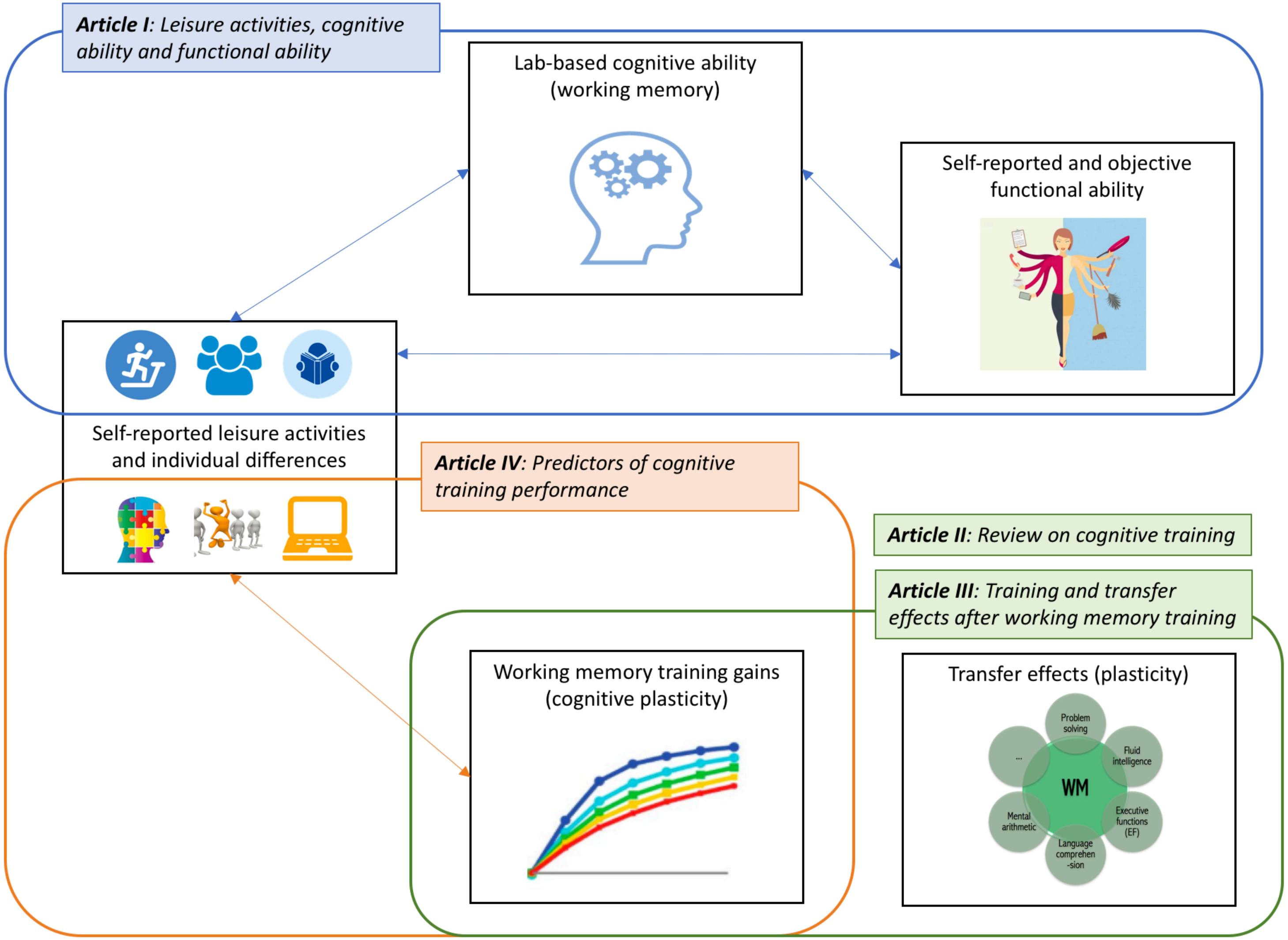

Figure 4. Overview of the four articles of this thesis.

ARTICLE I

3 FUNCTIONAL ABILITY IN EVERYDAY LIFE: ASSOCIATIONS WITH AN ENGAGED LIFESTYLE ARE MEDIATED BY WORKING MEMORY

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STATUS: IN PREPARATION

AUTHOR NOTE

During the work on her dissertation, Sabrina Guye was a pre-doctoral fellow of the International Max Planck Research School on the Life Course (LIFE; participating institutions: MPI for Human Development, Humboldt-Universität zu Berlin, Freie Universität Berlin, University of Michigan, University of Virginia, University of Zurich). This work was supported by grants awarded to the first author from the Suzanne and Hans Biäsch Foundation for Applied Psychology (Ref. 2014/32), the Forschungskredit of the University of Zurich (FK-16-062), and financial support from the URPP "Dynamics of Healthy Aging" of the University of Zurich.

3.1. ABSTRACT

Objectives: We aimed to test the hypothesis that the relation between an engaged lifestyle and functional ability is mediated through cognition. Cognition was conceptualized as working memory, and functional ability in everyday life as self-reported and objective everyday life performance. *Method:* Using data of 158 older adults, we first established the measurement model of working memory. Using a latent-variables approach, we then examined whether working memory mediated the relation between each of three indicators of an engaged lifestyle (i.e., intellectual, social and physical activities) and two indicators of functional ability in everyday life (i.e., self-reported cognitive and motor failures, and objective performance on everyday life tasks). *Results:* Working memory was found to fully mediate the relation between an indicator of intellectual activities (i.e., game playing) and objective functional ability in everyday life. Further, we found a negative association between physical activities (i.e., sports) and self-reported failures in everyday life, which was, however, not mediated through working memory. *Discussion:* Working memory is one pathway by which intellectual activities may be related to objective measures of functional ability in everyday life.

Keywords: Engaged lifestyle, working memory, functional ability, mediation

3.2. INTRODUCTION

Recently, the World Health Organization (WHO) published its first World Report on Ageing and Health (World Health Organization, 2015), proposing a theoretical framework on healthy aging that reflects an explicit process- and context-centered view. Healthy aging is defined as "the process of developing and maintaining the functional ability that enables well-being in older age". Functional ability is considered to be made up of physical and mental characteristics of the individual and its environment, as well as the interactions thereof. As such, the WHO emphasizes the importance of considering both interindividual differences and intraindividual variability in health characteristics (e.g., functional ability). Specifically, the WHO suggests focussing less on the level of symptoms and more strongly on functional ability in everyday life, including, but not exclusive to, the ability to be mobile in one's environment, to build and maintain relationships, and to learn and to make decisions. Accordingly, to define whether someone is aging in illness or health and to understand how healthy aging can be promoted, emphasis should be put more strongly on correlates and antecedents (e.g., an engaged lifestyle) as well as mechanisms (e.g., cognitive functioning) of functional ability in everyday life.

However, as yet, no study has examined if the association between activities of an engaged lifestyle and functional ability in everyday life are mediated by cognitive functioning in older adults. The present study fills this gap by investigating working memory (WM) as a potential mediator. WM is a cognitive system holding information available that is required for performing complex cognitive tasks and is strongly related to a number of complex cognitive real-world tasks in social (e.g., language and listening comprehension or storytelling) and intellectual contexts (e.g., logic learning or taking lecture notes; see Feldman Barrett et al., 2004 for an overview) and a number of higher-order cognitive abilities such as intelligence, shifting or inhibition (Kyllonen & Christal, 1990; Miyake & Shah, 1999).

3.2.1. LIFESTYLE AND FUNCTIONAL ABILITY

Only few studies examined the direct relationship between an engaged lifestyle and functional ability in daily life. Those studies that do exist often compare retrospective self-report assessments of both lifestyle and functional ability. For example, Cockburn and Smith (1991) found that an activity index consisting of social, domestic, and leisure activities was positively related to a number of self-reported memory items, such as the ability to remember first names and surnames, orientation, and face recognition. Further, a physically active lifestyle has been associated with increased self-reported functional ability in older adults (e.g., Kalisch et al., 2011; Kattenstroth, Kolankowska, Kalisch, & Dinse, 2010). Finally, participation in leisure activities and social engagement is related to reduced mortality (e.g., Lennartsson & Silverstein, 2001; Maier & Klumb, 2005).

3.2.2. Lifestyle and Cognitive Ability

An extensive amount of research has identified three clusters of everyday activities, namely intellectual, social, and physical activities (Harada et al., 2013; Hertzog et al., 2009) that are related to cognitive functioning. In general, these studies found that engagement in leisure activities is positively related to both cognitive ability and change, and negatively to the incidence of mild cognitive impairment or dementia (see Hertzog et al., 2009 for an overview). In addition, bi-directional effects have been reported, such as for intellectual and physical activities, and cognitive functioning (Daly et al., 2015; Small et al., 2012). Most research is based on correlational evidence and, thus, reverse causality cannot be ruled out: cognitively fitter individuals may also be those who engage in more everyday activities. There is some experimental evidence though from training studies suggesting the beneficial effects of an engaged lifestyle on cognition (Stine-Morrow et al., 2008; Tennstedt & Unverzagt, 2013).

3.2.3. Cognitive Ability and Functional Ability

Cognitive functioning has been proposed to be one of the most important antecedents of functional ability (e.g., Diehl, 1998; Schaie, Boron, & Willis, 2005). It has been found that fluid cognitive abilities, including reasoning, perceptual speed, and WM strongly correlate with both objective and self-reported measures of functional ability (Cockburn & Smith, 1991; Diehl, Willis, & Schaie, 1995), accounting for up to more than half of the variance found in everyday performance (Willis, Jay, Diehl, & Marsiske, 1992), with WM being one of the strongest correlates (Borella et al., 2017; Lewis & Miller, 2007).

3.2.4. The Present Study

In light of previous work that has shown evidence for bilateral relationships between how individuals spend their daily lives, their cognitive ability and how well they manage basic tasks of daily life, we set out to examine the three-fold associations that fit well with basic tenets of the WHO framework on healthy aging. We aim to (a) identify modifiable correlates (i.e., intellectual, social, and physical activities) of self-reported and objective functional ability in everyday life and to (b) uncover WM as one potential underlying mechanism of these associations.

To test our hypotheses, we used latent mediation analyses structural equation modeling (SEM). One advantage of SEM is that it separates true interindividual difference variance from variance caused by measurement error. Functional ability was assessed using self-reported and objective measures to overcome biases based on common method variance. Common method variance is variance referable to the measurement method rather than the construct of interest and can be troublesome if both the independent and dependent variables are assessed using the same measurement method (e.g., self-reported questionnaires; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Thus, our main objective is to investigate the relationship between an engaged lifestyle, cognitive ability, and functional ability in everyday life simultaneously.

3.3. METHODS

The data was collected in a previously reported WM training intervention study (Guye, De Simoni, & von Bastian, 2017; Guye & von Bastian, 2017 for detailed methods)

3.3.1. PARTICIPANTS

Participants were 158 older adults (79 females) aged 64 to 80 years (*M* = 70.41, *SD* = 3.62) who were recruited through the participant pool of the University Research Priority Program "Dynamics of Healthy Aging" of the University of Zurich, during lectures of the Senior Citizens' University of Zurich, flyers, online announcements, and word-of-mouth. They were paid CHF 150 (approx. USD 150) for participating in the training intervention. Exclusion criteria included psychiatric or neurological disorders, psychotropic drug use, severe motor, hearing or vision impairments potentially impacting cognitive functioning, color blindness (Ishihara, 1917), depression (GDS; Sheikh & Yesavage, 1986; cut-off = 4; *M* = 0.64, *SD* = 0.95), and cognitive impairment (MMSE; Folstein, Folstein, & McHugh, 1975; cut-off = 26; *M* = 29.23, *SD* = 0.85). Participants had to be retired, German speaking, and to have a computer with Internet connection at home. They were fairly well educated with a median education level of 4 (*MAD* = 2.97; range from 0 = *no formal education* to 7 = *doctorate*).

3.3.2. MEASURES

LEISURE ACTIVITIES

Intellectual, social, and physical engagement was assessed using an adapted version of the adult leisure activity questionnaire (Jopp & Hertzog, 2010). The adult leisure activity questionnaire included 54 activities and participants indicated how frequently they partook in each activity during the last two weeks on a 6-point Likert scale (1 = *never,* 2 = *occasionally,* 3 = *once a month,* 4 = *once a week,* 5 = *multiple times per week,* 6 = *daily*). These activities belonged to 11 activity domains, seven of which were used in this analysis (i.e., experiential, developmental, physical, social-private, and social-public activities, game playing, and technology use). The remaining four activity domains were not included in this data analysis, as they did not belong to one of the three activity clusters under study.

INTELLECTUAL ACTIVITIES. To assess intellectual engagement, we used the experiential domain *(i.e., "business not related to job", "collect stamps", "read for leisure", "read newspaper", "write letters",* and *"craft (e.g., sewing, knitting, crafts)",* the developmental domain *(i.e., "garden indoor or outdoor", "attend movies", "read books as part of job", "attend public lecture", "course at university", "creative writing (e.g., poems or books)", "go to library", "study foreign language",* and *"theatre, concerts, and exhibitions"),* the game playing domain *(i.e., "play knowledge games", "play board games", "play puzzles", "do cross-word puzzles",* and *"play card games"),* and the technology use domain *(i.e., "engage in photography", "play an instrument", "use computer software", "use electronic calculator", "arithmetic calculations",* and *"prepare own income tax").*

SOCIAL ACTIVITIES. To assess social engagement, we used the social-private domain (i.e., "*go out with friends", "visit friends or relatives", "attend parties (e.g., birthday"), "talk to friends or family on the phone", "give dinner for friends or family",* and "*eat out at restaurant"*), and the social-public activity domain (i.e., "*engaged in political activities", "give public talk", "attend club meetings", "attend organized social events",* and "*volunteer"*).

PHYSICAL ACTIVITIES. To assess physical engagement, we used the physical activity domain (i.e., "*weight lift and strength", "aerobics", "flexibility (e.g., stretching, yoga, tai chi)", "outdoor (e.g., sail, fish, walk, skiing)", "exercise (jog, bike, swim)",* and "*dance"*).

FUNCTIONAL ABILITY

We assessed both self-reported and objective everyday performance using established instruments as indicators for functional ability.

SELF-REPORTED EVERYDAY PERFORMANCE. The German version of the Cognitive Failure Questionnaire (CFQ; Broadbent, Cooper, FitzGerald, & Parkes, 1982; Klumb, 1995) is a self-report measure on 32 possible failures in perception (e.g., "*Do you fail to see what you want in a supermarket (although it's there)?*"), memory (e.g., "*Do you find you forget appointments?*"), and motor function (e.g., "*Do you drop things?*"). Participants had to indicate how often one of these failures occurred during the last couple of weeks on a 5-point Likert scale (0 = *never*, 1 = *very rarely*, 2 = *occasionally*, 3 = *quite often*, 4 = *very often*). The questionnaire was computer-based and the mean score across all items was used as dependent variable.

OBJECTIVE EVERYDAY PERFORMANCE. A German version of the Everyday Performance Test (EPT; Willis & Marsiske, 1993; cf. Guye & von Bastian, 2017) was used as an objective measure to assess individuals' ability to solve tasks encountered in activities of everyday life. Participants had to solve 15 everyday tasks, each consisting of two problems associated with the everyday tasks on printed material. To indicate their response, participants had to choose the correct out of four possible answers. The number of correctly solved problems within 45 minutes was used as dependent variable.

WORKING MEMORY

Six well-established tasks were used to assess WM: two tasks assessing storage and processing ability (complex span and Brown-Peterson), two tasks assessing binding ability, and two tasks assessing memory updating ability.

STORAGE AND PROCESSING. In the complex span task, participants had to memorize a series of positions of red squares presented in a 5 x 5 grid. We presented six trials per set size (2-4). Each trial of the series was interleaved by a distractor task, in which vertically or horizontally oriented L-shaped figures presented in the grid had to be rated according to their orientation (von Bastian & Eschen, 2016). In the Brown-Peterson task, participants had to memorize a series of Gabor patches. We presented four trials per set size (i.e., 2-4). The memorization phase was followed by a distractor task in which the length of a horizontally oriented bar had to be compared to a gap between two points (Brown, 1958; Peterson &

Peterson, 1959). Stimuli were presented for 1000 ms and the distractor task lasted maximally 3000 ms. Storage accuracy was used as the dependent measure.

BINDING. We used two versions of the binding task (Oberauer, 2005). In the triangles task, participants had to memorize a series of colored triangles at their locations in a 4 x 4 grid. In the shape task, participants had to memorize a series of colored shapes at their locations in a 1 x 4 grid. We presented six trials per set size in the first version and eight trials per set size in the second version of the task, with the set sizes ranging between 2 and 4. After memorization, positive probes (i.e., memorandum at correct location, 50% of probes) or negative probes (i.e., memorandum at wrong location or extra-list item, each 25% of probes) were presented. We used *d*' as the dependent variable.

MEMORY UPDATING. In the location-updating task (adapted from De Simoni & von Bastian, under revision), participants had to first memorize the locations of a set of circles in a 4 x 4 grid and then to update their positions by mentally shifting them to the adjacent cell based on the orientation of an arrow. We presented six trials per set size (i.e., 2-4). In the orientation-updating task, participants had to memorize the orientation of arrows pointing in one of eight directions (i.e., cardinal directions). Then, they were required to update the arrow's orientation by rotating them according to a presented arrow and indicate the new cardinal direction. We presented eight trials per set size (i.e., 2-4). Stimuli were presented for 500 ms and each updating step lasted 500 ms. Accuracy was used as the dependent measure.

3.4. RESULTS

Data and analyses scripts will be available on the Open Science Framework (OSF; https://osf.io/2jbpx). All analyses were conducted in R (version 3.2.3; R Core Team, 2016), latent mediation models were run with the lavaan package (0.5-23.1097; Rosseel, 2012). Descriptive statistics for the leisure activities, WM tasks, and the functional ability measures are listed in Table 1 (for correlations and reliabilities of the WM tasks see Table A1 in the Appendix A).

First, we evaluated the measurement model of the latent WM variable using confirmatory factor analysis. Second, we ran six models to test the relation between leisure activities (intellectual, social, or physical activities) and functional ability (self-reported or objective), and whether this association was mediated through WM. Age and education were included as covariates; the results remained qualitatively the same when excluding those variables though. All variables were *z*-standardized prior to the analyses.

Model fit was assessed using a combination of goodness of fit indices, including the Chi-Square goodness of fit test ($\chi2$), standardized root-mean-square residual (SRMR), root-mean-squared error of approximation (RMSEA) including its 90% credible interval (CI), and Comparative Fit Index (CFI). χ^2 values between 0 and $2df$ (and $p \geq .05$), SRMR $\leq .05$, RMSEA $\leq .05$, and CFI ≥ 0.97 are considered good fit, χ^2 values between $2df$ and $3df$ (and $p \leq .05$), SRMR $\leq .10$, RMSEA $\leq .08$, and CFI ≥ 0.95 are considered acceptable fit (Hu & Bentler, 1999; Schermelleh-Engel, Moosbrugger, & Müller, 2003). To obtain 95% bias corrected confidence intervals (95% CI), we used the bootstrap estimation approach (10,000 samples) implemented in lavaan.

Table 1

Descriptive Statistics

Measure	*M* ± *SD*	range	skew	kurtosis
	Leisure activities			
Experiential activities	3.32 ± 0.63	1.83 – 4.67	0.08	-0.62
Developmental activities	2.36 ± 0.48	1.33 – 3.67	0.28	-0.14
Game playing	2.59 ± 0.88	1.00 – 4.80	0.11	-0.68
Technology use	3.28 ± 0.79	1.33 – 5.33	0.12	-0.56
Social-private	3.18 ± 0.65	1.67 – 4.67	0.02	-0.39
Social-public	1.79 ± 0.56	1.00 – 3.50	0.72	0.06
Physical activities	3.11 ± 0.83	1.33 – 4.83	-0.04	-0.60
	Working memory			
Complex span Storage accuracy	0.27 ± 0.17	0.00 – 0.74	0.43	-0.68
Brown Peterson Storage accuracy	0.32 ± 0.15	0.00 – 0.75	0.23	-0.44
Memory updating locations Accuracy	0.39 ± 0.16	0.02 – 0.70	-0.04	-0.81
Memory updating arrows Accuracy	0.29 ± 0.16	0.08 – 0.79	0.62	-0.50
Binding triangles *d'*	1.00 ± 0.60	-0.61 – 2.54	0.16	-0.27
Binding shapes *d'*	1.06 ± 0.60	-1.08 – 2.68	-0.51	0.82
	Functional ability			
EPT	24.97 ± 3.73	9.00 – 30.00	-1.49	2.63
CFQ	2.19 ± 0.41	1.13 – 3.41	0.27	0.37

Note. EPT = Everyday Performance Test; CFQ = Cognitive Failure Questionnaire.

3.4.1. Measurement Model of Working Memory

The six WM tasks were specified to load on one latent WM factor, and this model yielded an acceptable fit $\chi^2(9) = 16.18$, $p = .063$, SRMR = .04, RMSEA = .07 [.00 - .13], CFI = .97. The standardized factor loadings were all significant (all *p*s < .001; complex span = .64, Brown-Peterson = .73, binding triangles = .66, binding shapes = .62, memory updating locations = .37, memory updating arrows = .73)

3.4.2. Latent Mediation Model

Six latent mediation models of WM as the mediator were tested, one for each combination of leisure activity indicators (i.e., intellectual, social, and physical engagement) and functional ability measures (i.e., self-reported and objective everyday performance). Figure

5 depicts an overview of the results. All models yielded an acceptable or good fit (see Table A2 in the Appendix A).

Leisure Activities, Working Memory, and Objective Everyday Performance

Table A3 in the Appendix A lists the detailed results for the models including objective everyday performance.

Intellectual Activities. We found that game playing was significantly positively related to WM (a_3 = 0.17, 95% CI [0.06 – 0.28], z = 3.09, p = .002) and that WM was significantly positively related to objective everyday performance (b = 0.65, 95% CI [0.40 – 1.01], z = 4.19, p < .001) suggesting that individuals who reported more game playing in their leisure time exhibited better WM, and that individuals with better WM showed better objective everyday performance. In addition, we found a significant total effect of game playing on objective everyday performance, c_3 = 0.18, 95% CI [0.03 – 0.33], z = 2.27, p = .023. Notably, this effect was no longer significant when including WM in the model (c'_3 = 0.06, 95% CI [-0.07 – 0.21], z = 0.88, p = .379), indicating that WM fully mediated the relationship. Indeed, the indirect effect of game playing on everyday performance through WM was significant, a_3*b = 0.11, 95% CI [0.04 – 0.19], z = 2.83, p = .005. Both age (b = -0.03, 95% CI [-.07 – -.00], z = 2.01, p = .044) and education (b = 0.13, 95% CI [0.06 – 0.19], z = 3.89, p < .001) were significantly related to WM. No other effects were significant.

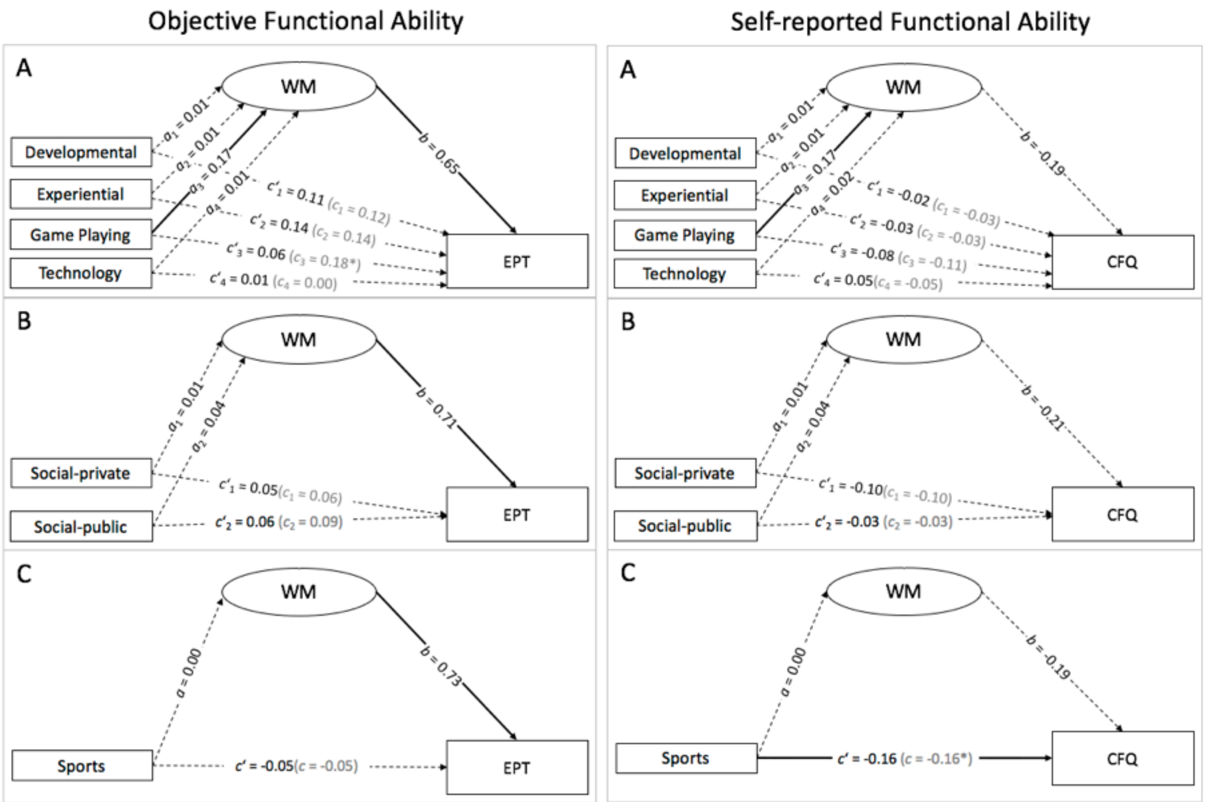

Figure 5. Schematic summary of the results of the mediation analyses, testing the mediating role of working memory for objective functional ability and self-reported functional ability. Panel A represents results for intellectual activities, panel B for social activities, and panel C for physical activities. Significant effects are indicated by solid arrows, non-significant effects by dotted arrows. Significant total effects (*c*-paths) are indicated by asterisk. WM = working memory; EPT = Everyday Performance Test; CFQ = Cognitive Failure Questionnaire. $*p < .05$, $**p < .01$, $**p \leq .001$.

Leisure Activities, Working Memory, and Self-reported Everyday Performance

Table A4 in the Appendix A lists the detailed results for the models including self-reported everyday performance.

Intellectual Activities. As for the objective indicator of functional ability, we found that game playing was significantly positively related to WM, indicating that individuals who reported more game playing in their leisure time also showed better WM performance ($a3$ = 0.17, 95% CI [0.06 – 0.28], z = 3.12, p = .002). Also, both age (b = -0.03, 95% CI [-0.07 – 0.00], z = 1.97, p = .049) and education (b = .13, 95% CI [0.06 – 0.19], z = 3.90, p < .001) were significantly related to WM, but no other effects – including the mediation - were significant.

Social Activities. Education (b = .11, 95% CI [0.05 – 0.16], z = 3.55, p <.001) but not age (b = -0.03, 95% CI [-0.06 – -0.00], z = 1.86, p = .064) was related to WM. Neither the association between social activities and self-reported everyday performance nor the mediation through WM or any other effects were significant.

PHYSICAL ACTIVITIES. We found a negative effect of sports on self-reported everyday performance (c = -0.16, 95% CI [-0.30 – -0.02], z = 2.26, p = .024), indicating that individuals who reported high levels of physical activities also reported fewer cognitive failures in everyday life. However, WM was neither associated with sports (a = 0.00, 95% CI [-0.10 – 0.11], z = 0.07, p = .943) nor self-reported everyday performance (b = -0.19, 95% CI [-0.56 – 0.10], z = 1.15, p = .251). Consequently, the indirect effect was also non-significant ($a*b$ = -0.00, 95% CI [-0.03 – 0.03], z = 0.05, p = .957) and the direct effect remained significant after including WM in the model (c' = -0.16, 95% CI [-0.30 – -0.01], z = 2.18, p = .029). Again, education (b = .11, 95% CI [0.05 – 0.17], z = 3.70, p < .001), but not age (b = -0.03, 95% CI [-0.06 – 0.00], z = 1.81, p = .071) was related to WM. No other effects were significant.

3.5. DISCUSSION

To the best of our knowledge, this study is the first to extend previous research on the effect of an engaged lifestyle, assessed via everyday leisure activities, on functional ability – conceptualized as self-reported and objective everyday performance – whilst considering WM as a potential mediator. We used data on self-reported intellectual, social, and physical leisure activities, objective and self-reported functional ability in everyday life, and multiple indicators to test our hypothesis.

3.5.1. ENGAGED LIFESTYLE AND FUNCTIONAL ABILITY

We found evidence that leisure activities are associated with functional ability in everyday life. More specifically, we found that one type of leisure activities, namely game playing in the intellectual domain, is associated with objective functional ability in everyday life and that physical activity is associated with self-reported functional ability in everyday life (potentially driven by the motor failures items of the cognitive failures questionnaire). This extends previous research, which has primarily focussed on the relationship between leisure activities and cognitive functioning and indicates that modifiable characteristics of older adults' everyday life, that is, whether they engage in intellectual or physical activities, are directly associated with how well they perform on everyday tasks and how they perceive their functional ability in daily life. This is especially crucial, as high levels of functional ability are regarded as a critical indicator of well-being in old age (e.g., Lawton et al., 1999). However, as our study was of cross-sectional nature, it does not allow to establish the directionality of these effects, and therefore derive recommendations for older adults, although based on theoretical frameworks (e.g., the enrichment hypothesis; Hertzog et al., 2009) it is plausible to argue that leisure activity engagement influences functional ability in everyday life, but bi-directional effects are possible as well.

3.5.2. Working Memory as Underlying Mechanism

Regarding WM, we found that it is associated with an indicator of intellectual activity, namely game playing, replicating earlier findings from previous cross-sectional research showing a positive relationship between game playing and cognition (e.g., Jopp & Hertzog, 2010) and evidence from longitudinal research suggesting that game playing activities can slow down cognitive decline across 5 years (e.g., Ghisletta, Lövdén, & Bickel, 2006) and can reduce the risk of dementia (e.g., Hughes, Chang, Vander Bilt, & Ganguli, 2010). Further, our results show that WM is associated with objective functional ability in everyday life and fully mediates the association between game playing and objective functional ability. The EPT strongly draws on analytical skills and participants have to actively store and process information to solve the everyday stimuli, a process that requires WM. This is in line with previous research showing that WM is strongly associated with EPT performance (Borella et al., 2017) and that WM training leads to improvements on EPT performance (Cantarella, Borella, Carretti, Kliegel, & de Beni, 2017). Thus, this finding expands previous literature by identifying the underlying mechanism linking intellectual activity and objective functional ability in everyday life. This has important implications for the everyday lives of older adults, because it highlights not only the importance of maintaining an active lifestyle, particularly in the intellectual domain, for maintaining high levels of functional ability in everyday life, but also illustrates that this association can be explained through WM ability.

Interestingly, the association between physical activity and self-reported functional ability in everyday life was not mediated through WM. Although there is some evidence for physical activity being positively associated with cognitive ability (e.g., Gow, Mortensen, & Avlund, 2012; Renaud, Bherer, & Maquestiaux, 2010) or exercise training enhancing cognitive functioning (e.g., Bherer et al., 2013 for a review), other studies did not find such a clear pattern (e.g., Dik, Deeg, Visser, & Jonker, 2003). One possibility for the absence of an effect of WM on self-reported measures of functional ability in everyday life is that the CFQ rather reflects the personality and affectivity of a person (e.g., if a person is worried about their cognitive or motor functioning) than actual cognitive or motor performance in everyday life. Indeed, in their study Karbach & Könen (under revision) found that while neuroticism and negative affectivity were related to CFQ performance, cognitive ability was not and they thus conclude that CFQ performance is related to impaired reflective thinking rather than cognitive functioning.

Surprisingly, however, most leisure activities were neither directly nor indirectly associated with both measures of functional ability in everyday life (i.e., experiential, developmental activities, technology use, public and private social activities). This pattern warrants further scrutiny, but, if replicated, indicates that only particular intellectual and physical activities may facilitate functional ability in daily life, and that the processes by which this association holds are only in part explained by WM.

3.5.3. LIMITATIONS AND FUTURE DIRECTIONS

Despite several strengths of the study such as considering a wide range of leisure activities, considering both objective and self-reported functional ability in everyday life, and assessing WM on the latent-variable level, we also acknowledge several limitations of the present work.

One major limitation of the present work is the cross-sectional nature of the study design. Hence, we could not establish the directionality of the relations between the variables under study. Future studies should adopt a longitudinal design to investigate the directionality of the effects to derive recommendations for older adults. Furthermore, the present study focused solely on interindividual differences. Longitudinal studies would allow for discriminating within- and between-person relationships of an engaged lifestyle and functional ability in everyday life, and the underlying mechanisms (e.g., cognition). One possibility would be to use ambulatory assessment technologies for assessing and modeling dynamic changes in leisure activity participation, cognitive performance, and functional ability status in everyday life.

A second limitation is that we used retrospective, self-reported measures of participation in leisure activities. Self-report measures are potentially prone to retrospective memory bias, especially in older adults. More objective tools such as smartphone accelerometers or GPS could be used to assess physical activity and mobility range; social interactions could be assessed with experience sampling tools such as the Electronically Activated Recorder (EAR; Mehl, Pennebaker, Crow, Dabbs, & Price, 2001). Such devices may provide more ecologically valid information on daily activities from naturalistic observations.

Further, although we accounted for the fact that leisure activity is not a unidimensional construct by differentiating between various activity domains (e.g., intellectual, social or physical activities), this approach prevented us from considering that some leisure activities might consist of multiple components. For instance, "playing knowledge games" (an item from the intellectual activity scale) probably also involves a considerable amount of social interaction. The exact determination and combination of activity components for each item is further complicated by individual differences in how these items are being interpreted. For instance, for person A doing sports is a merely physical activity that requires only minimal intellectual effort (e.g., running) and is done alone whereas for person B doing sports requires, besides the physical component, the memorization of complex coordinative processes and high levels of social engagement, as it is the case for group-based dancing or aerobics. Future studies should therefore make an effort to use measures that account for multiple components of leisure activities. We are confident that in addressing these limitations while following the methodological advantages of the present study, future work will be able to complement our initial findings and shed light on how inter- and intraindividual differences in how people live their lives relates to their cognition and overall functional capacity in daily life.

3.6. Conclusion

In closing, this study revealed that intellectual and physical leisure activities are significantly related to both objective and self-reported functional ability in everyday life. Further, we identified that the association between game playing and objective functional ability in everyday life is fully mediated by WM performance, suggesting that cognitive functioning is the mechanism underlying this association. This study replicates previous research on the importance of an engaged lifestyle for cognitive functioning, and extends it by highlighting the relation of intellectual and physical engagement for functional ability in everyday life.

3.7. APPENDIX A

SUPPLEMENTAL MATERIALS

Table A1

Correlations and Reliabilities of the Covariates, Working Memory Tasks, Functional Ability and Leisure Activity Measures

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Age	-															
2. Education	-.10	-														
3. Complex span	.00	**.27**	.91													
4. Brown Peterson	**-.16**	**.17**	**.35**	.76												
5. Memory updating locations	**-.21**	**.21**	**.46**	**.30**	.87											
6. Memory updating arrows	-.10	**.27**	**.39**	**.54**	**.46**	.93										
7. Binding triangles	-.13	.12	**.40**	**.39**	**.44**	**.49**	.59									
8. Binding shapes	-.11	.05	**.27**	**.26**	**.28**	**.20**	**.21**	.49								
9. Experiential	.12	.12	.07	.07	.08	.05	.04	-.09	-							
10. Developmental	.02	**.32**	.15	**.17**	.14	-.00	.06	.05	**.43**	-						
11. Game playing	.06	**-.18**	.12	.12	.12	.04	**.23**	**.17**	.11	.03	-					
12. Technology	.03	.02	.09	.09	-.02	.03	.00	.07	**.24**	**.27**	.10	-				
13. Physical	-.09	.14	-.04	**.16**	.01	.08	-.01	.00	.03	**.30**	-.08	.11	-			
14. Social-private	-.00	-.11	.02	.08	-.03	-.05	-.03	.02	**.21**	.15	**.17**	**.20**	.01	-		
15. Social-public	.04	**.22**	.11	.08	.05	.15	.01	-.08	**.30**	**.28**	.01	**.30**	**.17**	**.16**	-	
16. CFQ	**.16**	-.06	-.12	**-.16**	-.08	-.10	-.01	.05	-.05	-.04	-.10	.02	**-.17**	-.10	-.06	-
17. EPT	-.11	**.17**	**.21**	**.26**	**.36**	**.36**	**.30**	**.19**	**.22**	**.23**	**.16**	.09	-.02	.06	.12	-.08

Note. Correlation coefficients and reliabilities (only for the working memory measures) on the diagonal. Bold values represent significant Pearson correlations ($p < .05$). Reliabilities were computed using split-half reliability corrected with the Spearman-Brown's prophecy formula for the binding tasks, and Cronbach's alpha for complex span, Brown-Peterson, and updating tasks. CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test.

Table A2

Model Fit Indices for Mediation Models

	χ^2	*df*	*p*	SRMR	RMSEA [CI]	CFI
			Objective everyday performance			
Intellectual activities	62.87	46	.050	.04	.05 [.00 – .08]	.94
Social activities	44.17	36	.165	.04	.04 [.00 – .07]	.97
Physical activities	41.39	31	.101	.05	.05 [.00 – .08]	.96
			Self-reported everyday performance			
Intellectual activities	69.96	46	.013	.05	.06 [.03 – .08]	.90
Social activities	49.90	36	.062	.05	.05 [.00 – .08]	.94
Physical activities	47.19	31	.031	.05	.06 [.02 – .09]	.93

Table A3

Model Parameters for Latent Mediation Models with Objective Functional Ability as Dependent Measure

Model parameters	*b*	95% CI	*z*
Intellectual activities			
Effect on WM			
Developmental (a_1)	0.01	-0.11 – 0.13	0.20
Experiential (a_2)	0.01	-0.11 – 0.14	0.18
Game playing (a_3)	0.17**	0.06 – 0.28	3.09
Technology use (a_4)	0.01	-0.10 – 0.12	0.26
Effect of WM on EPT (*b*)	0.65***	0.40 – 1.01	4.19
Direct effect on EPT			
Developmental (c'_1)	0.11	-0.05 – 0.26	1.36
Experiential (c'_2)	0.14	-0.01 – 0.30	1.73
Game playing (c'_3)	0.06	-0.07 – 0.21	0.88
Technology use (c'_4)	0.00	-0.15 – 0.16	0.02
Indirect effect on EPT			
a_1*b	0.01	-0.07 – 0.09	0.20
a_2*b	0.01	-0.07 – 0.10	0.18
a_3*b	0.11**	0.04 – 0.19	2.83
a_4*b	0.01	-0.06 – 0.09	0.25
Total effect on EPT			
Developmental (c_1)	0.12	-0.06 – 0.28	1.35
Experiential (c_2)	0.14	-0.02 – 0.32	1.69
Game playing (c_3)	0.18**	0.03 – 0.33	2.27
Technology use (c_4)	0.01	-0.15 – 0.18	0.13
Social activities			
Effect on WM			
Social-private (a_1)	0.01	-0.11 – 0.12	0.10
Social-public (a_2)	0.04	-0.08 – 0.15	0.67
Effect of WM on EPT (*b*)	0.71***	0.44 – 1.10	4.29
Direct effect on EPT			
Social-private (c'_1)	0.05	-0.12 – 0.23	0.61
Social-public (c'_2)	0.06	-0.09 – 0.21	0.81
Indirect effect on EPT			
a_1*b	0.00	-0.08 – 0.09	0.10
a_2*b	0.03	-0.05 – 0.12	0.64
Total effect on EPT			
Social-private (c_1)	0.06	-0.13 – 0.26	0.59
Social-public (c_2)	0.09	-0.07 – 0.25	1.10
Physical activities			
Effect of sports on WM (*a*)	0.00	-0.10 – 0.11	0.06
Effect of WM on EPT (*b*)	0.73***	0.46 – 1.12	4.29
Direct effect of sports on EPT (*c'*)	-0.05	-0.19 – 0.09	0.71
Indirect effect on EPT (*a**b*)	0.00	-0.07 – 0.08	0.06
Total effect on EPT (*c*)	-0.05	-0.20 – 0.10	0.63

Note. WM = working memory; EPT = Everyday Performance Test.
**p* < .05, ***p* < .01, ***p* ≤ .001.

Table A4

Model Parameters for Latent Mediation Models with Self-Reported Functional Ability as Dependent Measure

Model parameters	*b*	95% CI	*z*
	Intellectual activities		
Effect on WM			
Developmental (a_1)	0.01	-0.11 – 0.13	0.23
Experiential (a_2)	0.01	-0.11 – 0.14	0.16
Game playing (a_3)	0.17**	0.06 – 0.28	3.12
Technology use (a_4)	0.02	-0.10 – 0.12	0.27
Effect of WM on CFQ (*b*)	-0.19	-0.55 – 0.12	1.09
Direct effect on CFQ			
Developmental (c'_1)	-0.02	-0.18 – 0.16	0.26
Experiential (c'_2)	-0.03	-0.22 – 0.16	0.34
Game playing (c'_3)	-0.08	-0.24 – 0.07	1.05
Technology use (c'_4)	0.05	-0.15 – 0.24	0.50
Indirect effect on CFQ			
a_1*b	-0.00	-0.03 – 0.03	0.17
a_2*b	-0.00	-0.04 – 0.03	0.12
a_3*b	-0.03	-0.10 – 0.02	1.09
a_4*b	-0.00	-0.03 – 0.03	0.20
Total effect on CFQ			
Developmental (c_1)	-0.03	-0.18 – 0.15	0.29
Experiential (c_2)	-0.03	-0.22 – 0.16	0.35
Game playing (c_3)	-0.11	-0.27 – 0.05	1.41
Technology use (c_4)	-0.05	-0.16 – 0.24	0.47
	Social activities		
Effect on WM			
Social-private (a_1)	0.01	-0.11 – 0.12	0.12
Social-public (a_2)	0.04	-0.07 – 0.15	0.69
Effect of WM on CFQ (*b*)	-0.21	-0.59 – 0.09	1.23
Direct effect on CFQ			
Social-private (c'_1)	-0.10	-0.28 – 0.08	1.09
Social-public (c'_2)	-0.03	-0.20 – 0.14	0.35
Indirect effect on EPT			
a_1*b	-0.00	-0.03 – 0.03	0.10
a_2*b	-0.01	-0.05 – 0.02	0.50
Total effect on CFQ			
Social-private (c_1)	-0.10	-0.27 – 0.08	1.14
Social-public (c_2)	-0.04	-0.20 – 0.13	0.45
	Physical activities		
Effect of sports on WM (*a*)	0.00	-0.10 – 0.11	0.07
Effect of WM on CFQ (*b*)	-0.19	-0.56 – 0.10	1.15
Direct effect of sports on CFQ (*c'*)	-0.16**	-0.30 – -0.01	2.18
Indirect effect on CFQ (*a**b*)	-0.00	-0.03 – 0.03	0.05
Total effect on CFQ (*c*)	-0.16**	-0.30 – -0.02	2.26

Note. WMC = working memory; CFQ = Cognitive Failure Questionnaire.
**p* < .05, ***p* < .01, ***p* ≤ .001.

ARTICLE II

4 PLASTICITY IN DIFFERENT AGE GROUPS: ADULTS LIFESPAN

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4.1. INTRODUCTION

There is robust longitudinal evidence for age-related decline in cognitive abilities. Fluid abilities are affected earlier than crystallized abilities, but with varying onset and slope between individuals (e.g., Salthouse, 2010). These negative age-related changes have sparked early interest in the possibility of preventing or counteracting this decline and thus maintaining cognitive health into later life with cognitive training interventions. In this chapter, we review the literature regarding training-induced plasticity in healthy older adults.

Many of the early training interventions focused on improving (episodic) memory ability, given that subjective changes in one's memory functioning are frequently voiced concerns from older adults (see also Wenger & Shing, 2016). Using a testing-the-limits paradigm, these training interventions typically instructed participants in a specific memory strategy, such as the method of loci, trying to uncover the strategy-independent latent performance potential and the boundary conditions for such latent reserve capacity of the aging cognitive system. The second generation of cognitive training interventions consisted of process-based approaches that focused on broader, more basic cognitive processes including working memory (WM; Könen, Strobach, & Karbach, 2016) or executive functions (Karbach & Kray, 2016). As a special form of process-based training, newer approaches target multiple cognitive domains simultaneously to achieve broader and larger transfer and greater ecological validity.

In the first part of this chapter, we review empirical evidence regarding the benefits of cognitive training interventions in healthy older adults separately for training gains, transfer, and their maintenance, as well as findings regarding brain structure and function. In the second part, we will outline key points to consider in future research to design more effective training interventions for healthy older adults to help maintain cognitive functioning.

4.2. BENEFITS OF COGNITIVE TRAINING INTERVENTIONS

Cognitive training studies differ on a multitude of design choices (e.g., type of training and its administration, cognitive domain, setting, intensity and duration, type of control group, and type of outcome measure to assess training effectiveness). In addition, the systematic reviews and meta-analyses available also differ substantially in their scope and inclusion criteria, and whether they distinguish between training gain and transfer effects and between different types of control groups. Thus, conclusions from these overview analyses are not straightforward to compare.

4.2.1. Evidence for Training Effects

Training Gains: Passive vs. Active Controls

Training effects are typically operationalized as pre- to post-training performance increases on the trained tasks compared to pre- to post-training performance changes in *passive* (i.e., with no instructed activity) or *active* control groups (i.e., with an instructed activity, but clear differentiation in the involved cognitive processes; Shipstead et al., 2012). Findings across different kinds of interventions indicate cognitive plasticity in terms of training gains (e.g., Baltes & Kliegl, 1992). For example, in their meta-analysis on process-based WM and executive functioning training, Karbach and Verhaeghen (2014) reported raw training gains of 0.9 *SD*, which remained almost equal in size when compared to passive controls (0.8 *SD*; see also Kelly et al., 2014 for similar effect sizes in WM and speed training interventions). Interestingly, however, training gains were found as reduced to 0.5 *SD* (Karbach & Verhaeghen, 2014) or even zero (Martin, Clare, Altgassen, Cameron, & Zehnder, 2011, see also Kelly et al., 2014 for a replication) after comparing to active controls. Promising training gains emerge for multi-domain training interventions (Park et al., 2014; see also Green, Gorman, & Bavelier, 2016).

Age-Related Differences in Training Gains

In contrast to findings from strategy-based training interventions indicating a magnification of age differences in cognitive performance and limits to training-induced plasticity in the very old (e.g., Verhaeghen & Marcoen, 1996), no such age differences in training gains were observed for process-based WM and executive functioning training interventions (Karbach & Verhaeghen, 2014). The implementation of complex cognitive strategies may require a higher level of cognitive functioning than is true for the elementary cognitive processes targeted in process-based training interventions (Verhaeghen, 2014). While research concerning multi-domain training is still in its infancy, there is initial evidence for greater video game training benefits for older-old compared to younger-old adults, but the underlying reasons are yet poorly understood (Green et al., 2016; Strobach & Schubert, 2016).

MODERATORS OF TRAINING EFFECTIVENESS

Group-based lab settings show greater effects than home-based training interventions (Kelly et al., 2014; Lampit et al., 2014), but it remains unclear whether these differences are due to formal vs. informal instruction or to the social setting vs. being alone. The same is true for training frequency and duration, where there is conflicting evidence about whether shorter or longer duration is most beneficial (Karbach & Verhaeghen, 2014; Kelly et al., 2014).

4.2.2. EVIDENCE FOR TRANSFER EFFECTS

As discussed in the paragraphs above, training interventions improve performance on the trained task, with greater gains compared to passive than active controls, and more robust effects for process- than strategy-based training interventions. Some of the training gains reported were of equivalent size as normal age-related declines across various cognitive domains, suggesting that training interventions likely help to reverse age-related declines and thus to stabilize cognitive functioning (Ball et al., 2002). The question is, however, if these improvements transfer to untrained tasks measuring either the same ability (i.e., near transfer) or to tasks measuring different abilities sharing underlying cognitive processes (i.e., far transfer; see, e.g., Noack et al, 2009; Shipstead et al., 2012).

TRANSFER TO OTHER COGNITIVE TASKS ASSESSED IN THE LABORATORY

For strategy-based trainings, little to no transfer effects have been found (Martin et al., 2011). It has been argued, though, that in contrast to the acquisition of specific memory strategies, practice effects from process-based training would be more prone to induce transfer to other cognitive tasks sharing the same core processes as the ones targeted in the intervention (e.g., Shipstead et al., 2012). Indeed, most process-based cognitive training interventions successfully lead to small to moderate near transfer effects when the training is adaptive and of longer duration (Kelly et al., 2014). For training interventions targeting WM and executive functioning, for example, Karbach and Verhaeghen's (2014) meta-analysis indicated a net gain in near transfer tasks compared to active controls of 0.5 *SD*. However, far transfer effects were very small (net far transfer effects 0.2 *SD* in Karbach & Verhaeghen, 2014). The few available multi-domain training interventions including cognitively complex group activities (e.g., Park et al., 2014), problem solving (Stine-Morrow et al., 2008), or video games (see Green, Gorman, & Bavelier, 2016; Strobach & Schubert, 2016) have also shown small to moderate transfer effects to some cognitive functions, including executive functioning, episodic memory, or processing speed. However, in order to design effective training interventions in the future, the understanding of the underlying processes, the cognitive functions targeted, and a high degree of ecological validity are necessary (see also Binder et al., 2015).

Transfer to Everyday Life

Transfer to everyday life has been examined in only few studies, and some recent reviews have even excluded studies with everyday transfer from their analysis (Lampit et al., 2014). When examined, everyday life has mainly been operationalized in terms of self-reported basic or instrumental activities of daily living (BADL/IADL) and, thus, measures of everyday competence impairments that are not necessarily optimal indicators of everyday functioning in healthy older adults due to ceiling effects. In the ACTIVE trial, the speed of information processing in everyday life was assessed by tasks such as looking up a telephone number, finding a respective food item on the supermarket shelf, identifying the ingredients on food labels, as well as self-reported driving ability. Not surprisingly, little to no evidence of transfer of the memory, reasoning, and processing speed training interventions to impairments in everyday functioning has been found immediately after training (Ball et al., 2002).

4.2.3. Evidence for Maintenance Effects

Most studies assess pretest and immediate posttest performance and transfer, but do not follow up on these effects over extended periods of time. Many studies examine maintenance only across a few months, even though it has been proposed that a 3-year interval is more appropriate for a sensitive test of maintenance and differential stability and change effects (Salthouse, 2006).

Maintenance of Training Gains

Kelly et al. (2014) report maintenance effects examined after up to 6 months, indicating maintenance of training gains following executive functioning and memory training interventions. Longer follow-up intervals have been included in selected studies, such as the ACTIVE trial (Rebok et al., 2014; Willis et al., 2006), covering 5-year and 10-year post-training assessments. In the ACTIVE study, training gains observed in each training group were maintained over 5 years, with indication of positive additional effects through intermediate booster training (Willis et al., 2006). After 10 years, training effects were maintained in the reasoning and processing speed domains, but no longer in the episodic memory domain (Rebok et al, 2014).

MAINTENANCE OF TRANSFER EFFECTS

Even though immediate or shorter-term effects after 2 years were not found in the ACTIVE trial (Ball et al., 2002), there are promising transfer effects to everyday functioning after longer periods for particular training conditions and everyday outcomes: (process-based) speed training was related to better driving performance and self-reported driving experience after up to 6-year intervals (Ball, Edwards, Ross, & McGwin, 2010). In addition, there is evidence for effects of training on the slope of change trajectories in everyday functioning: across a 5-year interval, participants in the (strategy-based) reasoning training group showed less steep declines in BADL/IADL competence and a 50 % reduced risk of experiencing a car accident compared to the passive control participants (Willis et al., 2006). After an extended time period of 10 years, ACTIVE data showed transfer to everyday functioning in terms of BADL/IADL for all three training conditions, suggesting that trained individuals experienced fewer impairments in their independent functioning in everyday life. Interestingly, at the long-term follow-up and an average age of 82 years, 60 % of the trained participants were at or above their baseline everyday competence level, which was true for only 50 % of the passive control participants. The summarized findings indicate that transfer effects on the ability to live independently apparently can become detectable or play out in the long run rather than immediately following the training intervention. Outcome measures assessing everyday performance above impairment level or everyday cognitive activities instead of abilities have hardly been used in the literature so far, but may be more promising to detect transfer to real life.

4.2.4. EVIDENCE FOR BRAIN STRUCTURE AND FUNCTION

Normal aging is accompanied by brain tissue loss and neurophysiological changes (Raz & Rodrigue, 2006). While the loss of gray matter manifests itself as general volume decline and cortical thinning (Fjell & Walhovd, 2010), the degradation of white matter is reflected in reduced integrity and the incidence of so-called white matter hyperintensities. With respect to brain function, aging has been linked with a complex pattern of local over- and underrecruitment of neural resources.

EFFECTS ON BRAIN STRUCTURE

A growing number of structural neuroimaging studies in healthy older adults provide evidence for beneficial effects of cognitive training on brain structure, especially for the domains of memory and WM, where most of the work has been carried out. These effects (compared to a control group) comprise reduced decreases, maintenance or even increases in volume or cortical thickness of brain structures relevant for the trained function (e.g., Lövdén, Schaefer, et al., 2012; Raz et al., 2013). The integrity of white matter, which can be qualified by different measures of water diffusion (e.g., fractional anisotropy, FA) on the basis of diffusion tensor imaging (DTI), can also be maintained or even increased by cognitive training interventions (Engvig et al., 2012). The reported effects reflect processes of structural neuroplasticity, which (partly) counteract the tissue degradation normally observed with aging. However, as most of the previous studies used passive control groups only, future studies including active control groups need to confirm the specificity of such effects.

EFFECTS ON BRAIN FUNCTION

The evidence emerging from studies investigating the effects of cognitive training interventions on brain function is less conclusive. On the one hand, studies adopting strategy-based training interventions report increased brain activity during post-training task performance (Nyberg et al., 2003). Based on the observed correlations between neurophysiological and behavioral changes, the activation increase has been attributed to an enhanced recruitment of task-specific regions that enables behavioral gains. On the other hand, process-based training studies, particularly in the domains of WM or executive functioning, showed decreased brain activity at post- compared to pre-training assessment, indicating improved neural efficiency during post-training task performance (e.g., Brehmer et al., 2011). This discrepancy in the pattern of activity might be due to the different neural mechanisms initiated by the different training types. However, there is evidence in younger adults that the activity decrease seen at later phases of process-based training interventions is actually preceded by an increase of activity in early training phases (Hempel et al., 2004). Future studies need to confirm whether this trajectory holds for older adults and whether strategy-based training interventions would also lead to increased neural efficiency after an extended period of implementing the acquired strategies.

Using electroencephalography (EEG), recent studies in older adults have demonstrated facilitative effects of cognitive training on early electrophysiological markers of the trained cognitive function with the extent of the ERP change predicting post-training performance (e.g., Berry et al., 2010).

4.3. What To Consider When Developing Future Training Interventions

Despite several promising results emerging from the field, a number of contradictory findings about training and transfer effects exist. However, the nature of this inconsistency remains unclear, and studies on key areas of training evaluation, including transfer to everyday performance and the embedding of training interventions into real-life contexts, are scarce at best. This section gives an overview on some methodological factors and individual differences that potentially influence training outcomes (see also Schmiedek, 2016, and for reviews see Noack et al., 2009; Shipstead et al., 2012; von Bastian & Oberauer, 2014). Moreover, this section highlights the importance of capturing daily life functioning in the context of cognitive training interventions and transfer assessments.

4.3.1. Methodological Issues

Sufficient Power

Low statistical power due to small sample sizes is a prevailing issue in training studies, which is especially pronounced in the field of gerontology. In Kelly et al.'s (2014) meta-analysis, nearly 60% of the included studies based their analyses on group sizes smaller than 40 participants. Bogg and Lasecki (2015) concluded that the mean power estimate across WM training studies is 11 %. This finding emphasizes that low statistical power increases the risk of false-negative results (i.e., missing effects by erroneously accepting the null hypothesis). Consequently, to correctly estimate the effectiveness of cognitive training interventions, it is crucial to conduct well-powered studies despite the logistical and financial challenges.

Active Control Groups

Using active control groups is still not common practice. Again, Kelly et al. (2014) reported that only 10 out of 24 studies included active control groups, whereas 14 studies relied on a no-intervention control group. However, passive control groups do not control for non-specific sources of improvement such as motivational aspects, expectancy effects, or effects from general cognitive stimulation. Consequently, passive controls do not allow to test for training-specific effects, but only control for test-retest effects. Thus, it is important that active control groups only differ in the process that is being trained, but are identical in all other intervention-specific factors that could potentially influence the size or scope of transfer in order to make a true evaluation of unique training effects possible.

ABILITIES INSTEAD OF SKILLS

The ultimate goal of cognitive training interventions in older age is to stabilize or enhance cognitive abilities relevant to everyday life. To ensure that training and transfer effects reflect changes in the underlying cognitive ability and not just particular task-specific skills, it is necessary to demonstrate transfer on the level of abilities by assessing it with multiple indicators (Noack et al., 2009). Ideally, change is evaluated on the latent level using structural equation modeling. Latent variables have the advantage of containing only the common variance (without the measurement error) among the tasks that are used as indicators, thus increasing the measurement validity.

4.3.2. INTER- AND INTRAINDIVIDUAL DIFFERENCES

Although the effectiveness of cognitive training interventions is typically examined at the group level, there is evidence indicating that individual differences such as personality traits (e.g., lower levels neuroticism and higher levels conscientiousness) and lower baseline cognitive ability are related to higher training and/or transfer effects (see Katz et al., 2016 and for a review see von Bastian & Oberauer, 2014). Further, at least in young adults, intraindividual couplings between affect and cognitive performance have been reported (e.g., Brose et al., 2012). However, it is important to note these concepts are not immutable, but underlie dynamic processes across the lifespan. For instance, personality undergoes changes from childhood until very old age. Interestingly, the trajectories across different personality traits are rather heterogeneous: whereas some traits show continuous mean-level increases (e.g., conscientiousness), others remain stable (e.g., social vitality; Roberts & Mroczek, 2008). Further, when it comes to affect, young and older adults show small differences in their average level of negative or positive affect typically favoring older adults, but they differ significantly in the amount of intraindividual affective variability and reactivity to daily events (e.g., Röcke, Li, & Smith, 2009). Still, studies investigating individual differences in the context of training in older adults are scarce.

To summarize, assessing inter- and intraindividual differences in the context of evaluating training-related effects is important for two reasons. Firstly, it deepens the understanding of possible moderators of the effectiveness of cognitive training interventions in older adults. Secondly, the identification of moderators is an important step toward individually tailored training approaches (see also Colzato & Hommel, 2016).

4.3.3. Capturing Daily Life in Training and Transfer

The majority of training studies has focused primarily on lab-based measures when examining cognitive abilities in older age. However, psychometric properties of commonly used transfer tasks measure *maximum performance*, that is, how participants perform when expending their maximum effort. Despite the consistent finding that younger adults outperform older adults in many of these lab-based tasks, many older adults report high levels of sense of control and life satisfaction, indicating that they successfully manage their daily lives (e.g., Scheibe & Carstensen, 2010). The disconnection between findings in cognitive functioning emerging from the lab (*maximum-level* cognition) and observations in daily life (*activity-based* cognition) is still understudied and not well understood (Verhaeghen, Martin, & Sędek, 2012).

In order to assess the effectiveness of a training intervention in older adults, it is therefore important to investigate cognitive improvements by including lab-based measures closer to everyday life. Preferably, though, it should be standard to systematically assess transfer in real life in addition to lab-based measures (Rebok et al., 2014). Similarly, a large part of the computer-based cognitive training interventions contains standard cognitive tasks. Another way to go *from lab to life* is to adopt video games or serious games containing tasks that more appropriately match everyday life challenges (Binder et al., 2015) or to directly engage in novel and cognitively demanding activities such as quilting or digital photography (Park et al., 2014; Stine-Morrow et al., 2008).

Cognitive training interventions often lack ecological validity, and comprehensive, reliable, and valid test batteries for assessing training-related improvements in real life are scarce (but see Mazurek, Bhoopathy, Read, Gallagher, & Smulders, 2015). In this vein, it could be beneficial for training researchers to join forces with aging researchers in examining the effects of older adults' living environments on cognition and overall functioning to find appropriate daily life training and transfer tasks (Wahl, Iwarsson, & Oswald, 2012).

ARTICLE III

5 WORKING MEMORY TRAINING IN OLDER ADULTS: BAYESIAN EVIDENCE SUPPORTING THE ABSENCE OF TRANSFER

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5.1. ABSTRACT

The question of whether working memory training leads to generalized improvements in untrained cognitive abilities is a longstanding and heatedly debated one. Previous research provides mostly ambiguous evidence regarding the presence or absence of transfer effects in older adults. Thus, to draw decisive conclusions regarding the effectiveness of working memory training interventions, methodologically sound studies with larger sample sizes are needed. In this study, we investigated whether or not a computer-based working memory training intervention induced near and far transfer in a large sample of 142 healthy older adults (65-80 years). Therefore, we randomly assigned participants to either the experimental group, which completed 25 sessions of adaptive, process-based working memory training, or to the active, adaptive visual search control group. Bayesian linear mixed-effects models were used to estimate performance improvements on the level of abilities, using multiple indicator tasks for near (working memory) and far transfer (fluid intelligence, shifting, and inhibition). Our data provided consistent evidence supporting the absence of near transfer to untrained working memory tasks and the absence of far transfer effects to all of the assessed abilities. Our results suggest that working memory training is not an effective way to improve general cognitive functioning in old age.

Keywords: cognitive training, working memory, healthy aging, Bayesian statistics

5.2. Introduction

On average, advancing age is accompanied by deterioration in multiple cognitive domains, with fluid abilities, such as processing speed, reasoning, and memory declining earlier than crystallized abilities (e.g., Horn & Cattell, 1967; Salthouse, 2004). In recent years, this has led to the development of computer-based cognitive training interventions, both in the "brain training" industry and in the cognitive training research community. The main goal of these interventions is to maintain or improve cognitive functions such as working memory (WM) that are relevant for daily life activities (e.g., Feldman Barrett et al., 2004). WM is a capacity-limited system coordinating representations needed for ongoing cognitive processing. Individual differences in WM capacity (WMC) have been shown to be strongly related to other higher-order cognitive abilities, including fluid intelligence, attention, shifting, inhibition (Kyllonen & Christal, 1990; A. Miyake et al., 2000; A. Miyake & Shah, 1999; Oberauer, Süß, Wilhelm, & Wittmann, 2008; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002), and a wide variety of complex everyday tasks (see Feldman Barrett et al., 2004 for an overview). On the basis of the process overlap theory (Kovavs & Conway, 2016), the theoretical rationale behind WM training is that extensive practice on a set of WM tasks enhances not only WMC, but also transfers to nontrained but related cognitive tasks or abilities that share cognitive processes with WM.

5.2.1. Inconclusive Evidence for the Effectiveness of Cognitive Training Interventions

"Brain training" interventions have proven popular especially among older adults as a promising way to counteract age-related cognitive decline, although there is little scientific support for the effectiveness of commercially available cognitive training interventions (see Simons et al., 2016 for a more detailed discussion). Regarding scientifically developed training interventions, numerous WM training studies have generated consistent evidence for large improvements in the trained tasks in younger and older adults alike (e.g., Karbach & Verhaeghen, 2014; Melby-Lervåg et al., 2016 for meta-analyses). Whether WM training leads to transfer effects, is, however, less clear. After some promising early findings reporting far transfer to, for instance, intelligence in younger adults (e.g., Jaeggi, Buschkuehl, Jonides, & Perrig, 2008), there is accumulating evidence against a generalized effect of WM training interventions in younger adults coming from methodologically sound studies (De Simoni & von Bastian, under revision; Redick et al., 2013, see also Melby-Lervåg & Hulme, 2013; Melby-Lervåg et al., 2016 for meta-analyses). Far fewer WM training studies exist that examined the effectiveness of WM training in older adults, the majority of which reported transfer effects to not explicitly practiced WM tasks (i.e., near transfer; Borella et al., 2014; Borella, Carretti, Riboldi, & De Beni, 2010; Brehmer, Westerberg, & Bäckman, 2012; Buschkuehl et al., 2008; Richmond, Morrison, Chein, & Olson, 2011), to untrained other cognitive abilities (i.e., far transfer; Borella et al., 2010; 2014; Brehmer et al., 2012), or to lab-based everyday life performance measures (Cantarella et al., 2017). So far, there are only few studies that have reported the absence of generalized transfer effects in older adults (e.g., von Bastian, Langer, et al., 2013). Thus, a recent meta-analysis concluded that, compared with active controls, WM and executive control training leads to substantial training and near transfer, and to smaller but significant far transfer effects (Karbach & Verhaeghen, 2014, but see Melby-Lervåg et al., 2016).

The absence of studies reporting null findings may indicate that older adults are more susceptible to WM training interventions than younger adults, as there might be more room for improvement for individuals starting at lower levels of baseline performance and subsequently benefitting more from training. However, it is also possible that methodological shortcomings (e.g., small sample sizes) or design choices (e.g., transfer assessment, the nature of the control group) in the reported studies caused these effects. Most training studies in older adults are severely underpowered due to small sample sizes (e.g., meta-analysis of Lampit et al., 2014; median group size of 22), which is associated with two major statistical problems (cf. von Bastian, Guye, & De Simoni, in press). On the one hand, low power can drastically inflate effect sizes of individual studies (Halsey, Curran-Everett, Vowler, & Drummond, 2015), leading to biased estimates in meta-analyses evaluating the overall effect of cognitive training (Bogg & Lasecki, 2015). On the other hand, *p*-values can vary greatly in the presence of small sample sizes (referred to as "the dance of the *p*-value" by Cumming, 2011), with the low statistical power increasing the risk of not only false-negative, but also false-positive findings (Button et al., 2013). A suitable alternative to the traditional *p*-value is the Bayes factor (BF), which is the ratio between the likelihood of the data under one hypothesis (typically the alternative hypothesis, H_1) relative to another hypothesis (typically the null hypothesis, H_0). Considering the controversy regarding the (in-)effectiveness of cognitive training interventions, BFs offer an important advantage. Whereas significant *p*-values indicate the presence of a hypothesized effect, nonsignificant *p*-values only indicate the absence of evidence for a hypothesized effect. Hence, nonsignificant *p*-values do not distinguish between evidence for the null hypothesis and the lack of evidence for either of the two hypotheses. In contrast, BFs allow for drawing conclusions about the evidence supporting the presence of an effect (i.e., whether the data are more likely under the alternative hypothesis), the evidence supporting the absence of an effect (i.e., whether the data are more likely under the null hypothesis), or whether there is not enough evidence to support either of the two hypotheses sufficiently, as indicated by ambiguous BFs (for a more detailed discussion, see, e.g., Dienes, 2014). Thus, BFs constitute an adequate statistical index in the context of intervention research.

So far, only few studies have applied BFs to evaluate the effectiveness of cognitive training (but see De Simoni & von Bastian, under revision; Guye et al., 2017; Sprenger et al., 2013; von Bastian & Oberauer, 2013). On the basis of the meta-analysis from Au et al., (2015), Dougherty et al. (2016) reevaluated the effectiveness of *n*-back training in terms of far transfer to intelligence in younger adults using BFs. They demonstrated that studies with passive control groups strongly favored the alternative hypothesis (i.e., the presence of the effect), but those with active controls moderately favored the null hypothesis (i.e., the absence of the effect). In a similar vein, to investigate the (in-)effectiveness of WM training interventions in older adults, we reevaluated the meta-analysis from Lampit et al. (2014) using Bayesian statistics. Our results show that overall, most studies produced only ambiguous evidence regarding near and far transfer effects, providing insufficient statistical support for either the alternative or the null hypothesis (von Bastian et al., in press). Thus, the debate of whether or not WM training is effective in older adults cannot be settled on the basis of the current body of literature.

In addition, poor design choices such as the nature of transfer assessment or the control group can further limit the inferences permitted by individual studies (cf. Guye et al., 2016; Noack et al., 2009; Shipstead et al., 2012). For example, many studies relied on only single indicators when assessing transfer, thereby potentially mistaking task-specific effects with generalized transfer effects (e.g., Borella et al., 2010; 2014; Brehmer et al., 2012). As each task contains paradigm-specific variance, stimulus material-specific variance, and some measurement error, using multiple indicators per cognitive ability and thus inferring from a combined score, minimizes random sources of error (cf. Moreau, Kirk, & Waldie, 2016). Another issue is the lack of adequate control groups. Although a passive control group sufficiently controls for the test repetition effects (and therefore allows for testing potential effects of any kind of cognitive stimulation), it cannot do so for unspecific intervention effects (e.g., regularly spending time on a computer, social contacts during the assessments, changes in training-related motivation or beliefs). Controlling for such effects requires an active control group that engages in an alternative, plausible training intervention comparable to the experimental training intervention that only differs in the ability that is being trained by keeping all other intervention-specific and -unspecific factors constant (e.g., duration, intensity, adaptive task difficulty, stimulus material).

In sum, although a number of training studies with older adults have been published in recent years, the evidence regarding transfer effects is still relatively ambiguous in either direction (i.e., presence or absence of transfer effects; cf. von Bastian et al., in press). Thus, before concluding about the general effectiveness of WM training in older adults, methodologically sound studies (i.e., adequate control group and transfer assessment) with large samples are needed to provide decisive evidence for or against transfer effects.

5.2.2. THE PRESENT STUDY

The main goal of this study was to investigate training and transfer effects after a process-based WM training intervention in older adults using Bayesian statistics by overcoming the methodological issues outlined above. We conducted a randomized controlled, double-blind study trial and assigned the participants to either the experimental (WM) group or to an active control group practicing visual search (VS). As previous research found that conjunction search efficiency is unrelated to WMC (e.g., Kane, Poole, Tuholski, & Engle, 2006), VS training constitutes a plausible cognitive control condition (cf. Harrison et al., 2013; Redick et al., 2013). The training interventions were comparable in length and duration, as both groups received five weeks of intensive training intervention consisting of 25 training sessions. WM training consisted of heterogeneous WM tasks, thereby enhancing variability and reducing the probability that participants merely adopt task-specific processes (cf. Schmidt & Bjork, 1992). On the basis of work by Wilhelm, Hildebrandt, and Oberauer (2013), we selected three well-established WM tasks shown to be reliable indicators of the WM construct, namely an updating task, a binding task, and a complex span task. For both training interventions, solely visuospatial stimulus material was used to prevent the application of verbal strategies such as imagery or rehearsal (cf. Zimmermann, von Bastian, Röcke, Martin, & Eschen, 2016). On the basis of the assumption that plasticity is driven by a prolonged mismatch between task demands and cognitive capacity (Lövdén et al., 2010), we implemented an adaptive training algorithm in both training groups that increased the level of difficulty depending on participants' performance.

The effectiveness of the WM training intervention in eliciting training, near and far transfer effects was evaluated using BFs, as they allow for quantifying the strength of evidence for the alternative hypothesis (i.e., presence of training/transfer effects) and the null hypothesis (i.e., absence of training/transfer effects). Training effects were quantified by administering test versions of the WM and VS training tasks in addition to measuring performance improvements during training, as the latter is potentially confounded with initial level of performance (cf. von Bastian & Oberauer, 2013). Transfer effects were assessed by comparing pre- and post-training performance in multiple tasks per cognitive ability (cf. Shipstead et al., 2012). Near transfer was measured using three structurally dissimilar visuospatial WM tasks. Further, we assessed far transfer to multiple measures of fluid intelligence, shifting, and inhibition. Fluid intelligence has been shown to be strongly correlated with WM (Engle, Tuholski, Laughin, & Conway, 1999; Salthouse & Pink, 2008; Süß et al., 2002), and both shifting, the ability encompassing control processes in situations where individuals actively switch between tasks (for an overview, see Monsell, 2003), and inhibition, the ability to suppress inappropriate behavioral responses, share common variance with WM updating according to Miyake et al.'s three-factor model of executive functions (Miyake et al., 2000).

5.3. METHOD

5.3.1. PARTICIPANTS

Older adults (range: 65–80 years; M = 70.35, SD = 3.66) were recruited through the participant database of the University Research Priority Program (URPP) "Dynamics of Healthy Aging" of the University of Zurich, lectures at the Senior Citizens' University of Zurich, flyers, online announcements, and word-of-mouth. Interested seniors were informed that they would participate in a "brain jogging" study and that they had the right to withdraw at any time. Written informed consent was obtained from all participants. The study was approved by the ethics committee of the Department of Psychology of the University of Zurich (in compliance with the Helsinki Declaration).

Participants were retired, German speaking seniors who had access to a computer with Internet connection at home and basic experience in using the computer and Internet. After study completion, they received CHF150 (approximately USD$150). We refrained from using estimates from previous training studies for power analyses, as they are likely severely underpowered (Bogg & Lasecki, 2015), and therefore, probably yielded inflated effect size estimates (Halsey et al., 2015). Instead, we aimed to recruit at least three times as many participants than previous training studies with older adults (i.e., n = 66 per group; cf. Lampit et al., 2014). A total of 194 seniors were individually screened for ongoing neurological and psychiatric disorders, psychotropic drug use, and severe sensory impairments (motor, hearing, or vision disabilities) potentially impacting cognitive performance. Further, participants were screened for color blindness using the Ishihara Test (Ishihara, 1917), for subclinical depression using the German version of the Geriatric Depression Scale (GDS; Sheikh & Yesavage, 1986: cut-off criterion = 4), and for cognitive impairment using the German version of the Mini-Mental State Examination (MMSE; Folstein et al., 1975: cut-off criterion = 26). During the screening session, participants additionally completed three computer-based questionnaires, including a demographic questionnaire, a health questionnaire, and a questionnaire assessing computer and Internet experience. In addition, everyday problem solving abilities were assessed using an adapted version of the multiple-choice Everyday Problems Test (EPT; Willis & Marsiske, 1993). The EPT is an objective measure for the ability to solve everyday activities on printed material. Results on the EPT are reported elsewhere (Guye et al., 2017).

Three participants were ineligible for the study due to self-reported psychotropic drug use, self-reported psychiatric disease, and subclinical depression symptoms as assessed by the GDS, respectively. Of the remaining 191 participants, 16 participants withdrew their participation during the everyday life assessment due to the reasons shown in Figure 6. The remaining 175 participants entered the subsequent study phase (i.e., preassessment, training, and postassessment), 17 of which withdrew their participation before beginning with the training intervention (attrition rate of 10%). During the training intervention, 2 additional participants (one of each training group) withdrew their participation due to low training motivation (approx. 1%). Further, we had to exclude 14 participants: the first 6 participants of the study had to be excluded as they were administered a longer test battery during preassessment including additional tasks, which we afterward decided to remove due to time restrictions. Data from 6 participants were excluded as they did not complete one or more tasks during cognitive pre- or postassessment. Moreover, two individuals were excluded because they performed below chance level in more than 25% of the training sessions. Thus, the final sample consisted of 142 participants (68 female, 74 male).

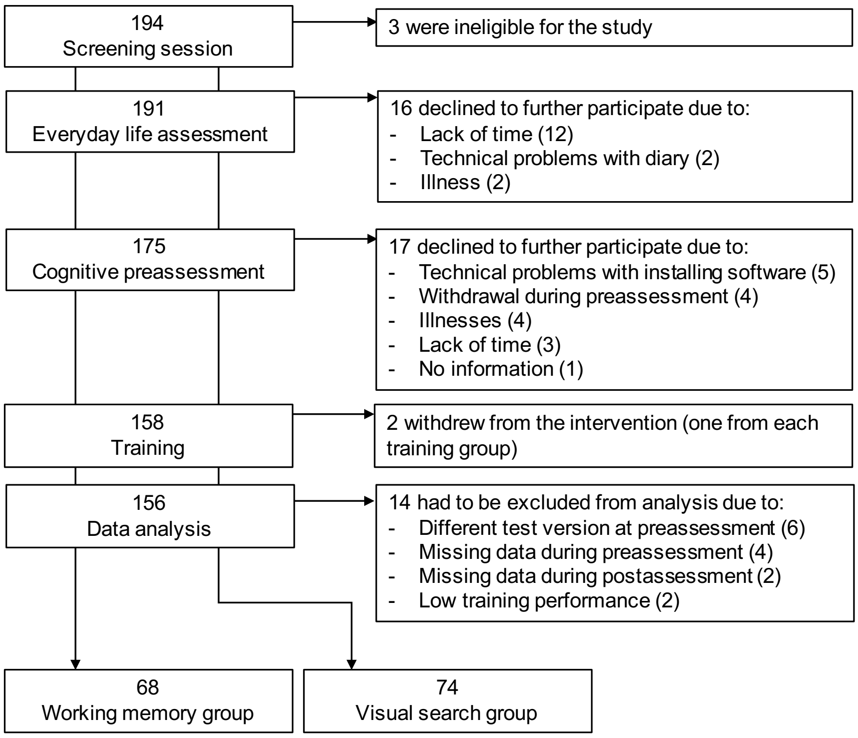

Figure 6. Flowchart of participant recruitment.

To assign participants to groups, they were given a random identification number. A randomization list was created stratified by age (ranges: 65–69, 70–74, 75–80) and gender. A random sequence of experimental group and active control group assignments was generated within each age and gender group and participants were assigned accordingly by the research manager. As listed in Table 2 (see Table B1 in the Appendix B for null hypothesis significance testing [NHST] results), the two groups were comparable in age, education, cognitive functioning (MMSE), and depressive symptoms (GDS), with ambiguous evidence regarding group differences in education (with the experimental group, on average, having obtained a slightly higher degree), and in gender (with more females in the control group).

Table 2

Participant Demographics

	Group				
Demographics	WM	VS	BF_{H0}	BF_{H1}	Error
Gender (f/m)	29 / 39	39 / 35	2.38	0.42	0.00
Age (years)	70.15 (3.57)	70.53 (3.75)	**4.66**	0.21	0.00
Education [a]	4.47 (1.77)	3.96 (1.67)	1.33	0.76	0.00
MMSE score	29.16 (0.78)	29.28 (0.93)	**4.01**	0.25	0.00
GDS score	0.68 (1.09)	0.64 (0.87)	**5.39**	0.19	0.00

Note. Mean values and standard deviations in parentheses. Bold Bayes factor values indicate substantial evidence for the respective hypothesis. Bayes factors were determined by Bayesian two-tailed independent *t*-tests (chi-square test in the case of gender). WM = working memory; VS = visual search; BF = Bayes factor; H_0 = null hypothesis; H_1 = alternative hypothesis; MMSE = Mini-Mental State Examination; GDS = Geriatric Depression Scale.

[a] The scale for education ranged from 0 (*no formal education*) to 7 (*doctorate*).

5.3.2. Design and Material

Table 3 lists the four phases of the study: (1) an everyday life assessment, (2) a cognitive preassessment, (3) an intensive training regime, and (4) a cognitive postassessment. We used a randomized controlled double-blind pretest/posttest trial comparing the WM group with the VS group. Neither the participants nor the research assistants collecting the outcome measures had knowledge of the group to which they were assigned, and participants were not informed about the existence of a second condition.

Table 3

Overview of the Study Phases

Study phase	Description	# of sessions	Duration
Everyday life assessment	Longitudinal daily life assessment and questionnaires	4	4 hours
Cognitive preassessment	Extensive cognitive test battery including 21 tasks for working memory, inhibition, shifting, fluid intelligence, and visual search; affect questionnaire	1	4.5 hours
Cognitive training	25 sessions of computer-based cognitive training	25	30-45 min per session
Cognitive postassessment	Extensive cognitive test battery including 21 tasks for working memory, inhibition, shifting, fluid intelligence, and visual search; Training-related expectations questionnaire.	1	4.5 hours

Note. Everyday life assessment and cognitive training were self-administered and cognitive pre- and post-assessments were conducted in-lab.

Everyday Life Assessment

Eligible participants took part in a longitudinal daily life assessment and completed several questionnaires. During the 1-week daily life assessment, participants were asked to complete a modified and translated online version of the day reconstruction method (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) at three predefined days. To assess general activity involvement, participants were asked to complete a modified version of the Adult Leisure Activity Questionnaire (Jopp & Hertzog, 2010). In addition, participants completed several questionnaires including the NEO Five-Factor Inventory (Costa & McCrae, 1992), Grit scale (Duckworth, Peterson, Matthews, & Kelly, 2007), Need for Cognition scale (Cacioppo & Petty, 1982), Theories of Intelligence scale (Dweck, 2000), General Self-Efficacy scale (Schwarzer & Jerusalem, 1995), and the Cognitive Failure Questionnaire (Broadbent et al., 1982), results of which are reported elsewhere (Guye et al., 2017).

Cognitive Training Interventions

Training procedures were identical for both groups if not mentioned otherwise. The interventions were self-administered at home using Tatool (von Bastian, Locher, & Ruflin, 2013). After each session, data were automatically uploaded to a webserver running Tatool

Online, allowing for monitoring participants' compliance throughout the training phase.

Participants were instructed to complete 25 sessions of intensive cognitive training (30 min to 45 min per session) distributed equally across 5 weeks, with most participants completing training sessions on 5 days a week. To enhance training commitment, participants were individually reminded via e-mail if they fell behind their training schedule. Moreover, at the beginning of every training week, participants received an e-mail with information on their training status and a motivating slogan (e.g., "If you always do what you've always done, you'll always get what you've always got"). In case of technical problems, participants could contact the study manager via phone or e-mail.

Participants practiced three cognitive tasks, each lasting approximately 10 min per session. Task order was randomized to avoid sequence effects. Each task was automatically terminated if task duration exceeded 15 min to prevent training sessions longer than 45 min. Before each session, participants were asked to complete a shortened version of the Positive and Negative Affect Schedule Expanded Form (PANAS-X; Grühn, Kotter-Grühn, & Röcke, 2010) assessing their current affect. They had to indicate their agreement or disagreement with the adjectives on an 8-point Likert scale. At the beginning of and midway through training (sessions 2 and 14), we assessed participants' training motivation using an adapted version the Intrinsic Motivation Inventory (Deci & Ryan, 2016). Results of affective and motivational correlates during training will be the focus of a future article.

WORKING MEMORY TRAINING. Training consisted of a complex span task, a binding task, and a memory updating task (see Figure 7). For all three tasks, the set size (i.e., number of memoranda) and the response time limit varied depending on the level of task difficulty set by the adaptive training algorithm (see the following text). In each session, participants completed up to 15 trials per task.

COMPLEX SPAN TASK. We used the figural-spatial complex span task from von Bastian and Eschen (2016). In each trial, participants had to memorize a series of positions of red squares in a 5 x 5 grid. Presentation of memoranda was interleaved by a distractor task, in which participants had to determine as quickly and as accurately as possible whether an L-shaped figure composed of red grid cells was oriented vertically or horizontally. At the end of each trial, participants had unlimited time to recall the grid positions in correct serial order by mouse-click. Memoranda were presented for 1,000 ms each. Response time during the distractor task was limited (see adaptive task difficulty).

BINDING TASK. We used an adapted version of the local recognition task (e.g., Oberauer, 2005), in which participants had to memorize a series of colored triangles and their position in a 4 x 4 grid. Afterward, as many probes as memoranda were presented, for each of which participants had to decide whether it matched the triangle that was previously presented at that position. Across all 15 trials, 50% of the probes were positive, 25% were distractors (i.e., triangles in colors not presented within this trial), and 25% were intrusions (i.e., triangles in colors that had been presented within this trial but at a different position). Memoranda were displayed for 900 ms (with an additional 100-ms interstimulus interval) and time to respond was restricted (see adaptive task difficulty).

MEMORY UPDATING TASK. We used an adapted version of the task used by De Simoni and von Bastian (under revision; cf. Schmiedek, Lövdén, & Lindenberger, 2014). First, participants had to memorize the locations of colored circles presented simultaneously in a 4 x 4 grid. Thereafter, one of the circles appeared on a white background alongside an arrow. Participants had to update the circle's position by mentally moving it to the adjacent cell in the direction the arrow pointed toward (up, down, left, or right). Participants indicated the new position of the circle by mouse click. Each trial consisted of nine updating steps of which four to five were switch and repetition trials, respectively. During switch trials, the to-be-updated circle changed compared with the preceding trials, whereas during repetition trials the to-be-updated circle did not change. Memoranda were displayed for 500 ms and time to respond was restricted (see adaptive task difficulty).

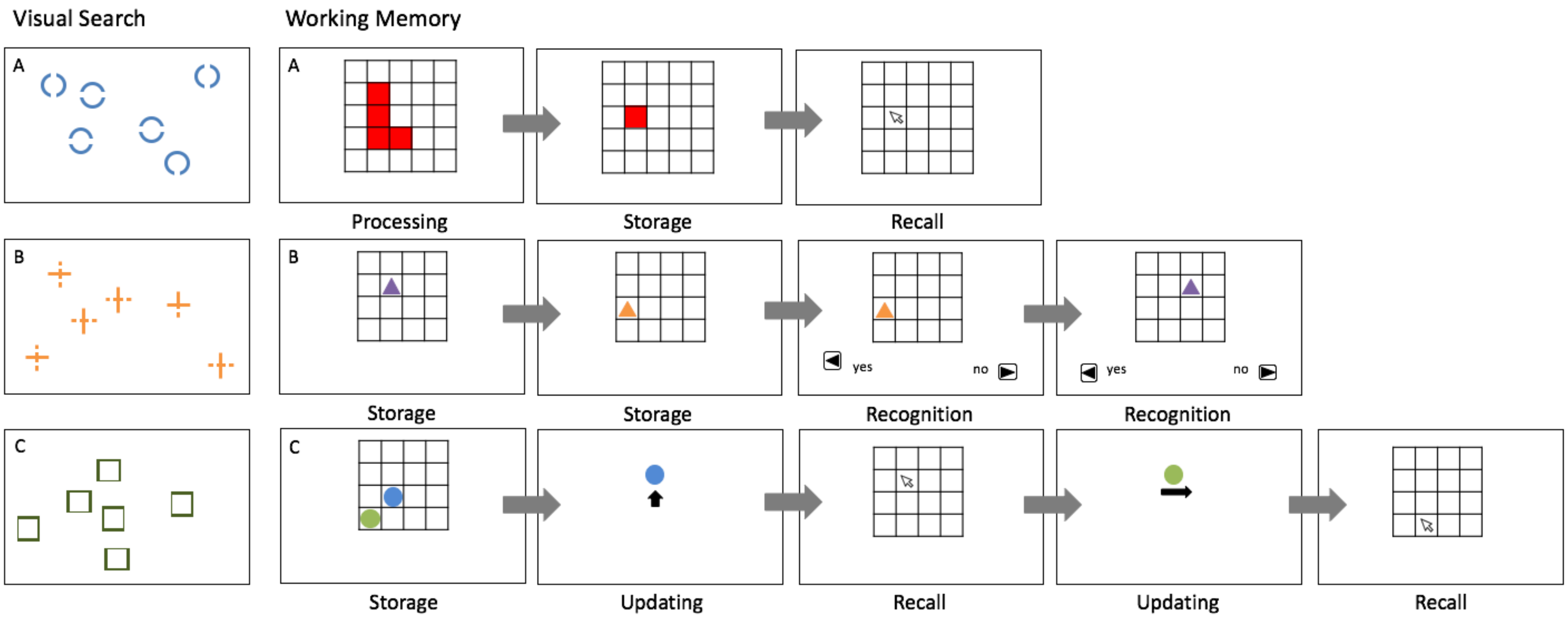

Figure 7. Schematic overview of the visual search training tasks: A) circles task, B) crosses task, C) rectangles task and the working memory training tasks: A) complex span task, B) binding task, C) memory updating task.

Visual Search Training. On the basis of Kane et al.'s (2006) experiments, we developed three conjunction search tasks to improve visual search tasks using different stimulus material such as circles, crosses, and rectangles (cf. De Simoni & von Bastian, under revision). Participants had to identify a target stimulus as quickly and as accurately as possible among distractors. All stimuli appeared in a warped 8 x 7 grid, resulting in an irregular distribution of the stimuli on the screen. For each task and each session, one half of the trials contained a target.

In the circles task (cf. von Bastian, Langer, et al., 2013) the target stimulus was a circle with a gap facing up, right, down, or left. Distractors were circles with two gaps either facing left and right, or up and down. In the crosses task, the target stimulus was a cross with a gap at the upper, right, lower, or left bar. Distractors were crosses with two gaps either at the left and right bar, or at the upper and lower bar. Finally, in the rectangles task, the target stimulus was a rectangle with a bold side facing up, right, down or left. Distractors were rectangles with two bold sides either facing left and right, or up and down. Participants had to indicate the presence of a target by pressing the corresponding arrow key or by pressing the A key if there was no target present during the trial. Participants completed up to 70 trials per task and time to respond was unrestricted.

Adaptive Task Difficulty. We used the default adaptive score and level handler included in Tatool (von Bastian, Locher, et al., 2013). In the first training session, participants' performance was assessed and task difficulty possibly increased after every 7% of trials (one trial in WM training and five trials in VS training), ensuring participants to quickly reach their individual baseline cognitive capacity limit and so maximizing the time exposed to challenging task demands. After the first session, performance was assessed and task difficulty possibly after every 40% of trials (six trials in WM training and 28 trials in VS training). In the WM tasks, difficulty was raised by either reducing the response time limit by 300 ms (four subsequent level-ups) or by increasing the set size by one additional memorandum (fifth level-up, which also reset the response time limit) if accuracy was above 80%. The first training session started with a set size of two and a response time limit of 5,000 ms per response. The maximum set size was set to eight for the three tasks. In the VS tasks, level of difficulty was raised by increasing the number of distractors by two if participants' accuracy was above 95%. The start level of difficulty was six items, the maximum set size was set to 54 for the three tasks.

Training Feedback. Performance-based trial-by-trial feedback was presented as a green check mark for a correct response, and a red cross for an incorrect response. Moreover, at the beginning of each session, participants were presented with their performance across all completed training sessions in the form of a graph plotting level against session for each of the three training tasks.

COGNITIVE ASSESSMENT

Before and after the training intervention, participants completed an extensive test battery (see Table 4 for task descriptions and Table B2 in the Appendix B for correlations and reliabilities). Cognitive pre- and postassessment were conducted at the University of Zurich in the laboratories of the URPP "Dynamics of Healthy Aging" by trained research assistants. Participants were tested in groups of up to four individuals. Both pre- and postassessments took 4.5 hr, including a 10-min break and two 5-min breaks.

To measure training-related improvements independent of the training situation, we used criterion tasks identical to those practiced during WM and VS training. Near transfer was assessed with structurally dissimilar WM tasks and different visuospatial stimulus material. Far transfer was measured to fluid intelligence, shifting, and inhibition. We used identical versions of the test battery at both cognitive assessments to facilitate comparability between the groups and test occasions.

At the beginning of the pretraining assessment, participants completed a shortened version of the PANAS-X (Grühn et al., 2010) assessing their general affect. At the end of the postassessment, self-reported training-related expectations were assessed with three items asking participants whether they believed that they improved in the trained tasks, in the untrained cognitive tasks, and in everyday life tasks. Participants had to respond on an 8-point Likert scale ranging from *not at all* to *very much*.

Cognitive tasks and the affect questionnaire were programmed using Tatool (von Bastian, Locher, et al., 2013), the expectation questionnaire was in paper-pencil format. Participants completed the pre- and postassessment within 7 days before respectively after the scheduled training phase.

Table 4

Description of the Cognitive Test Battery Used During Training and Cognitive Assessments

Measure	Task	Number of trials	Timing	Dependent measure
		Working Memory Criterion		
Complex span	Memorize a series of positions of red squares presented in a 5 x 5 grid. Each trial of the series was interleaved by a distractor task, in which vertically or horizontally oriented L-shaped figures presented in the grid had to be rated according to their orientation (von Bastian & Eschen, 2016).	6 per set size (i.e., 2-4)	Stimulus duration: 1000 ms Distractor task: max. 3000 ms	Storage accuracy
Binding	Memorize a series of associations between coloured triangles and their locations in a 4 x 4 grid. After memorization, memoranda and probes were presented, each of which had to be rated as positive or negative. Across all trials, 50 % of the probes were positive (i.e., matches), and 50 % were negative (25 % distractors, and 25 % intrusions; adapted from Oberauer, 2005).	6 per set size (i.e., 2-4)	Stimulus duration: 900 ms + 100 ms inter-stimulus-interval	*d*’[a]
Memory updating	Memorize the locations of a set of circles in a 4 x 4 grid. Then, update the circle’s positions by mentally shifting them to the adjacent cell based on the orientation of an arrow (adapted from De Simoni & von Bastian, under revision; Schmiedek et al., 2014).	6 per set size (i.e., 2-4)	Stimulus duration: 500 ms Updating step duration: 500 ms	Accuracy
		Visual Search		
Circles	Identify the circle with one gap among circles with two gaps (adapted from Kane et al., 2006).	8 per set size (i.e., 7-11)	Unrestricted response time	Accuracy
Crosses	Identify the cross with one gap among crosses with two gaps (adapted from Kane et al., 2006).	8 per set size (i.e., 7-11)	Unrestricted response time	Accuracy
Rectangles	Identify the rectangle with one bold side among rectangles with two bold sides (adapted from Kane et al., 2006).	8 per set size (i.e., 7-11)	Unrestricted response time	Accuracy

	Working Memory Transfer			
Brown-Peterson	Memorize a series of Gabor patches. Memorization phase was followed by a distractor task, in which the length of a horizontally oriented bar had to be compared to a gap between two points (Brown, 1958; Peterson & Peterson, 1959).	4 per set size (i.e., 2-4)	Stimulus duration: 1000 ms Distractor task: max. 3000 ms	Storage accuracy
Binding	Memorize a series of associations between coloured shapes and their locations in a 1 x 4 grid. After memorization, memoranda and probes were presented, each of which had to be rated as positive or negative. Across all trials, 50 % of the probes were positive (i.e., matches), and 50 % were negative (25 % distractors, and 25 % intrusions; adapted from Oberauer, 2005).	8 per set size (i.e., 2-4)	Stimulus duration: 900 ms + 100 ms inter-stimulus-interval	*d'*[a]
Memory updating	Memorize the orientation of arrows pointing in one of eight directions (i.e., cardinal directions). Then, update the arrow's orientation by rotate them according to a presented arrow and indicate the new cardinal direction (adapted from De Simoni & von Bastian, under revision; Schmiedek et al., 2014).	8 per set size (i.e., 2-4)	Stimulus duration: 500 ms Updating step duration: 500 ms	Accuracy
	Fluid Intelligence			
RAPM	Out of nine options, identify the missing element that completes a 3 x 3 pattern matrix (Arthur & Day, 1994).	12	Task restricted to 12 minutes	Accuracy
Relationships	Out of five options, select the correct Venn diagram that represents the relationship among a set of three objects (Ekstrom, French, Harman, & Derman, 1976).	2 x 15	Each block max. 4 min	Accuracy
Locations	Based on four dashed lines, identify the rule of the spatial distribution of x's and place the x at the corresponding location on a fifth dashed line (Ekstrom et al., 1976).	2 x 14	Each block max. 6 min	Accuracy

		Shifting[b]		
Animacy-size (categorical)	Categorize drawings of animals and everyday objects according to two classification rules: animacy (living vs. non-living) and size (smaller vs. larger than a soccer ball; (von Bastian, Souza, & Gade, 2016).	Single blocks: 64 Mixed block: 128	Cue stimulus interval: 150 ms Unrestricted response time	Proportional SC[c] and MC[d]
Shape-color (figural)	Categorize geometrical shapes according to two classification rules: color (green vs. blue) and shape (round vs. angular; von Bastian et al., 2016).	Single blocks: 64 Mixed block: 128	Cue stimulus interval: 150 ms Unrestricted response	Proportional SC[c] and MC[d]
Parity-magnitude (numerical)	Categorize digits (1-9, excluding 5) according to two classification rules: parity (odd vs. even) and magnitude (smaller vs. greater than 5; von Bastian et al., 2016).	Single blocks: 64 Mixed block: 128	Cue stimulus interval: 150 ms Unrestricted response time	Proportional SC[c] and MC[d]
		Inhibition		
Flanker	Indicate the orientation of a centrally presented target arrow, which is flanked by congruent (arrows facing toward the same direction), incongruent (arrows facing toward the opposite direction) or neutral stimuli (i.e., "XX"; Eriksen & Eriksen, 1974).	96 per condition (i.e., neutral, congruent, incongruent)	Unrestricted response time	Proportional interference[e]
Stroop	Indicate the hue of a color word while inhibiting the prepotent response to read the word instead. In congruent trials, the hue matches the color word, in incongruent trials, the hue does not match the color word, and in neutral trials, a neutral stimulus (i.e., "xxxxx") is presented (Stroop, 1935).	96 per condition (i.e., neutral, congruent, incongruent)	Unrestricted response time	Proportional interference[e]
Simon	Indicate the color of a green or red circle which is presented on the left, right, or in the center of the screen by pressing the corresponding arrow key (e.g., left for green circles, right for red circles). The circle can appear on the congruent (e.g., green circle on the left), incongruent (e.g., red circle on the left) or neutral position (i.e., centrally; Simon, 1969).	96 per condition (i.e., neutral, congruent, incongruent)	Unrestricted response time	Proportional interference[e]

Note. RAPM = Raven Advanced Progressive Matrices; SC = switch costs; MC = mixing costs
[a] *d'* = z(hit rate) – z(false alarms to intrusions). [b] Shifting tasks consisted of five blocks presented in the following order: two single blocks, a mixed block, and two single blocks in reversed order. A visual cue indicating the classification rule was presented before the stimulus. In single block tasks, the same rule had to be applied across all trials, whereas in mixed blocks, stimuli

had to be classified according to both rules which switched unpredictably. Half of the trials were repetition trials (two successive trials in which the same rule had to be applied) and the other half were switch trials (the rule changed from the preceding to the current trial). [c] Difference between RTs in the switch trials of the mixed block and RTs in the repetition trials of the mixed block divided by their average. [d] Difference between RTs in the repetition trials of the mixed block and RTs of the single blocks divided by their average. [e] Difference between RTs of the incongruent trials and RTs of the neutral trials divided by the average RT across all trials.

5.4. RESULTS

Data are available on the Open Science Framework (OSF; osf.io/zrj3q). Data preprocessing and data analysis were carried out with R (Version 3.2.3; R Core Team, 2016). BFs were computed using the R package "BayesFactor" (version: 0.9.12.2; Rouder & Morey, 2012) and the default prior settings (i.e., Cauchy distribution with a medium scaling factor, r = 0.707). To test the robustness of our results, we replicated the analyses across a range of priors (i.e., r = 0.50, r = 2.00) and the conclusions remained the same. The interested reader is referred to the analyses scripts publicly available on the OSF. BFs range from zero to infinity, with higher values expressing stronger evidence for the respective hypothesis. An adapted version of the verbal labels proposed by Wetzels and Wagenmakers (2012) was used to facilitate interpretation (see Table 5). BFs favoring the null hypothesis (i.e., BFs < 1) are expressed as 1/BF.

Table 5

Verbal Labels for Bayes Factors

BF	Interpretation
> 100	Decisive
30-100	Very strong
10-30	Strong
3-10	Substantial
1-3	Ambiguous
1	No evidence

Note. Adapted from Wetzels and Wagenmakers (2012). BF = Bayes factor.

5.4.1. PREPROCESSING OF THE REACTION TIME DATA

Shifting scores (i.e., proportional switch costs [SC] and mixing costs [MC]) and inhibition scores (i.e., proportional interference) were computed based on the reaction times (RTs) of correct responses. RT outliers were excluded from the data analysis. Outliers were defined as data points that were more than three median absolute deviations away from the overall median (Leys, Ley, Klein, Bernard, & Licata, 2013).

5.4.2. TRAINING COMPLIANCE AND PERFORMANCE

Due to scheduling problems, seven participants completed less than 25 sessions. Three participants from the WM group completed 21, 23, and 24 sessions and 4 participants from the VS group completed 19, 20, and 24 (2 participants) sessions. As all of these participants completed at least 75% of the training intervention, they were included in the data analysis to enhance power.

There was substantial evidence that the WM (M = 24.97, SD = 0.71; range = 21–28) and VS group (M = 24.88, SD = 0.95; range = 19–26) did not differ in the number of completed training sessions as indicated by a Bayesian two-tailed independent t-test, BF_{H0} = 4.57 = 0.00%, (see Table B3 in the Appendix B for NHST results). If participants completed more than 25 training sessions, these additional sessions were omitted from data analysis.

As illustrated in Figure 8, both groups showed substantial training effects for each training task. To test if performance improved monotonically across sessions, we conducted Bayesian linear mixed effects (LME) models with set size achieved by the end of each session as the dependent variable and training session (coded as linear contrast) as fixed effect (see Table B4 in the Appendix B material for NHST results). These analyses were run separately for each group and training task, including a random effect for subject to account for variability between individuals. The reported estimates represent the increase in set size from one session to the next around their 95% credible interval. There is decisive evidence that across the 25 training sessions, participants in the WM group improved in the binding task (M_{Diff}= 0.09 [0.08, 0.09]), BF_{H1} > 100 ± 0.98%, the complex span task (M_{Diff} = 0.07 [0.07, 0.07]), BF_{H1} > 100 ± 1.01%, and the memory updating task (M_{Diff} = 0.04 [0.04, 0.04]), BF_{H1} > 100 ± 1.92%. The VS group also improved training performance in the circles task (M_{Diff} = 1.35 [1.33, 1.38]), BF_{H1} > 100 ± 3.17%, the rectangles task (M_{Diff} = 1.52 [1.50, 1.55]), BF_{H1} > 100 ± 1.22%, and the crosses task (M_{Diff} = 1.39 [1.37, 1.42]), BF_{H1} > 100 ± 2.15%.

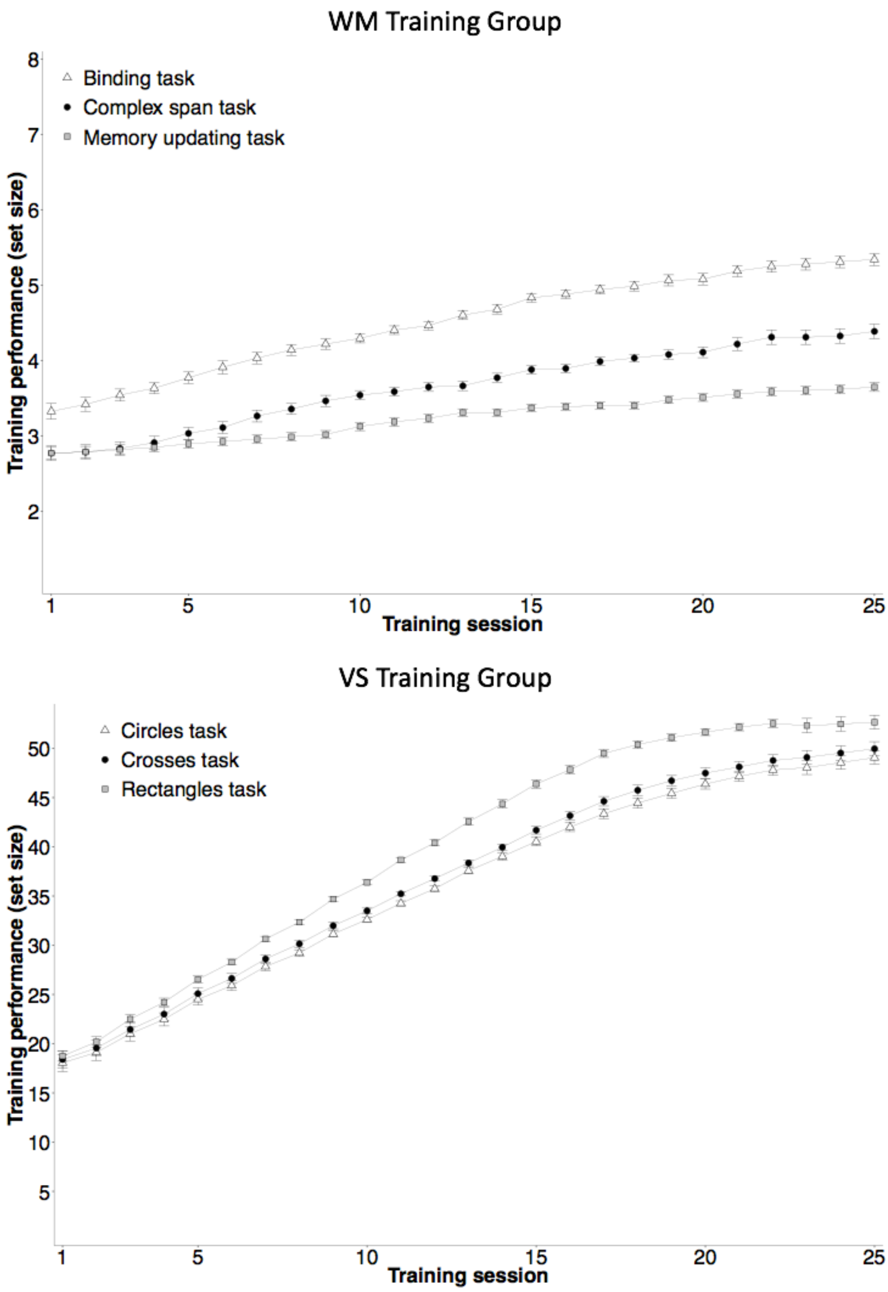

Figure 8. Training performance during working memory and visual search training. Maximum set size for the working memory training group was 8 items, and 54 items for the visual search training group. Error bars represent 95% within-subjects confidence intervals calculated according to Cousineau (2005) and Morey (2008). WM = working memory; VS = visual search.

5.4.3. Training Gains and Transfer Effects

To investigate training gains, we assessed performance improvements for both groups on the respective test versions of the training tasks (i.e., WM and VS criterion tasks). Moreover, we evaluated whether WM training led to near transfer to structurally dissimilar WM tasks, and to far transfer to fluid intelligence, shifting, and inhibition.

Statistical Modeling

To assess performance improvements from pre- to postassessment while taking potential baseline differences into account, we calculated standardized gains scores for each cognitive task (i.e., postassessment performance subtracted by preassessment performance divided by the preassessment standard deviation), which were used as dependent variables (cf. von Bastian & Eschen, 2016; von Bastian & Oberauer, 2013). Bayesian LME models including crossed random effects were run to estimate performance improvements on the level of cognitive abilities (as compared with individual cognitive tasks; cf. Baayen, Davidson, & Bates, 2008; Judd, Westfall, & Kenny, 2012 for details). Training group was included in the models as fixed effect predictor. Two random effects were included to account for variability between the participants and to account for variability between the tasks. The reported estimates represent the group differences in gain scores around their 95% confidence interval. Descriptive statistics of the cognitive tasks are presented in Table 6.

Comparability at Baseline

To ensure that the training gains and transfer effects can be attributed to the training intervention and do not reflect baseline group differences, we compared the groups at preassessment running Bayesian LME models with crossed random effects for each ability using the preassessment scores as dependent variables (see Table 7 see Table B5 in the Appendix B for NHST results). There was no evidence for baseline differences for most abilities, although evidence was ambiguous for the WM criterion ($BF_{H0} = 2.13 \pm 1.74\%$), WM transfer ($BF_{H1} = 1.02 \pm 1.66\%$), and shifting SC tasks ($BF_{H1} = 1.59 \pm 1.46\%$). Further inspection of the individual tasks revealed that there was strong evidence for a baseline difference for the shifting SC categorical task only ($BF_{H1} = 9.90 \pm 0.00\%$), with the VS group outperforming the WM group (see Table B6 in the Appendix B for BFs and NHST). As group differences in training gains and transfer effects were assessed using standardized gain scores, any effects observed were beyond these baseline differences. However, results should still be interpreted cautiously as we cannot exclude regression to the mean for these outcomes.

Table 6

Descriptive Statistics of Cognitive Task Performance

	WM		VS	
Task	Preassessment	Postassessment	Preassessment	Postassessment
Criterion				
Complex span	.31 (.18)	.73 (.16)	.26 (.16)	.30 (.19)
Binding	1.06 (0.65)	1.29 (0.65)	0.98 (0.58)	1.10 (0.57)
Memory updating	.41 (.17)	.65 (.12)	.37 (0.15)	.46 (.16)
Visual search				
Circles	.96 (.08)	.96 (.09)	.95 (.09)	.99 (.02)
Crosses	.83 (.23)	.88 (.20)	.89 (.19)	.99 (.02)
Rectangles	.91 (.17)	.90 (.19)	.91 (.18)	.98 (.06)
Working memory				
Brown-Peterson	.35 (.14)	.42 (.15)	.31 (.15)	.36 (.16)
Binding	1.12 (0.67)	1.52 (0.61)	0.99 (0.55)	1.27 (0.52)
Memory updating	.33 (.17)	.38 (.16)	.28 (.15)	.32 (.18)
Fluid Intelligence				
RAPM	.41 (.16)	.48 (.20)	.37 (.16)	.41 (.18)
Relationships	.43 (.16)	.47 (.16)	.42 (.13)	.44 (.15)
Locations	.26 (.12)	.33 (.14)	.26 (.11)	.33 (.12)
Shifting SC				
Categorical	-.27 (.16)	-.26 (.14)	-.20 (.12)	-.23 (.14)
Figural	-.22 (.13)	-.23 (.12)	-.18 (.15)	-.20 (.13)
Numerical	-.27 (.26)	-.28 (.19)	-.24 (.26)	-.26 (.24)
Shifting MC				
Categorical	-.56 (.22)	-.50 (.17)	-.59 (.23)	-.55 (.16)
Figural	-.68 (.22)	-.68 (.18)	-.70 (.23)	-.69 (.19)
Numerical	-.54 (.28)	-.48 (.22)	-.53 (.24)	-.55 (.24)
Inhibition				
Flanker	-.03 (.05)	-.03 (.11)	-.03 (.04)	-.02 (.04)
Stroop	-.19 (.11)	-.18 (.10)	-.19 (.13)	-.19 (.12)
Simon	-.05 (.02)	-.04 (.02)	-.05 (.03)	-.04 (.02)

Note. Values are means with standard deviations in parentheses. Scores are accuracies (proportion correct), except for shifting (proportional switch costs and mixing costs), binding (*d'*), and inhibition (proportional interference). WM = working memory; VS = visual search; RAPM = Raven Advanced Progressive Matrices; SC = switch costs; MC = mixing costs.

Table 7

Group Baseline Differences in Cognitive Abilities

Ability	M_{Diff} [95% HDI]	BF_{H0}	BF_{H1}	Error
Criterion	0.20 [-0.05, 0.47]	2.13	0.47	1.74
Visual search	-0.03 [-0.26, 0.22]	**9.09**	0.11	2.07
Working memory	0.25 [0.01, 0.49]	0.98	1.02	3.66
Fluid intelligence	0.11 [-0.11, 0.33]	**6.25**	0.16	1.57
Shifting SC	-0.28 [-0.52, -0.03]	0.63	1.59	1.46
Shifting MC	0.06 [-0.17, 0.29]	**9.09**	0.11	1.40
Inhibition	0.04 [-0.18, 0.25]	**10.00**	0.10	2.42

Note. Estimates are means of the sampling from the posterior distribution with 10,000 iterations based on standardized data assessed by Bayesian linear mixed-effects models. As standardized values were used the grand mean for all abilities is zero. Bold Bayes factors values indicate substantial evidence for the presence or absence of baseline group differences. HDI = highest density interval of the posterior distribution; BF = Bayes factor; H_0 = null hypothesis; H_1 = alternative hypothesis; SC = switch costs; MC = mixing costs.

Training Gains

Results for the Bayesian LME models are presented in Table 8 (see Table B7 in the Appendix B for NHST results). We found decisive evidence for an effect of group for the WM criterion tasks, indicating that the WM group improved more from pre- to postassessment compared to the VS group (M_{Diff} = 1.14 [0.93, 1.35], $BF_{H1} > 100 \pm 1.63\%$). Similarly, we found strong evidence for an effect of group for the VS criterion tasks, indicating that the VS group improved more from pre- to postassessment on the trained VS tasks compared to the WM group (M_{Diff} = -0.41 [-0.67, -0.15], $BF_{H1} = 11.74 \pm 2.29\%$).

Transfer Effects

Results for Bayesian LME models are presented in Table 8 (see Table B7 in the Appendix B for NHST results). We found substantial evidence for the absence of an effect of group for near transfer to structurally dissimilar WM tasks (M_{Diff} = 0.12 [-0.07, 0.33], BF_{H0} = 5.26 ± 2.56%). Moreover, there was substantial to strong evidence for the absence of an effect of group on measures of far transfer, including fluid intelligence (M_{Diff} = 0.08 [-0.14, 0.30], BF_{H0} = 8.33 ± 1.60%), shifting SC (M_{Diff} = 0.11 [-0.10, 0.33], BF_{H0} = 6.67 ± 1.50%), shifting MC (M_{Diff} = 0.11 [-0.12, 0.34], BF_{H0} = 6.67 ± 2.48%), and inhibition (M_{Diff} = -0.02 [-0.25, 0.24], BF_{H0} = 11.11 ± 1.50%).

Table 8

Group Differences in Gain Scores

Ability	M_{Grand}	M_{Diff} [95% HDI]	BF_{H0}	BF_{H1}	Error
Criterion	0.89	1.14 [0.93, 1.35]	< 0.01	**> 100**	1.63
Visual search	0.27	-0.41 [-0.67, -0.15]	0.09	**11.74**	2.29
Working memory	0.40	0.12 [-0.07, 0.33]	**5.26**	0.24	2.56
Fluid intelligence	0.38	0.08 [-0.14, 0.30]	**8.33**	0.12	1.60
Shifting SC	-0.06	0.11 [-0.10, 0.33]	**6.67**	0.15	1.50
Shifting MC	0.10	0.11 [-0.12, 0.34]	**6.67**	0.15	2.48
Inhibition	0.08	-0.02 [-0.25, 0.24]	**11.11**	0.09	1.50

Note. Estimates are means of the sampling from the posterior distribution with 10,000 iterations based on standardized data assessed by Bayesian linear mixed-effects models. Bold Bayes factor values indicate at least substantial evidence for the presence or absence of group differences. HDI = highest density interval of the posterior distribution; BF = Bayes factor; H_0 = null hypothesis; H_1 = alternative hypothesis; SC = switch costs; MC = mixing costs.

Training-Related Expectations

Bayesian two-tailed independent *t*-tests were used to test whether the groups differed in their training-related expectations. Data from four participants were missing for the item on “expected cognitive transfer” and data from three participants were missing for the item on “expected transfer to everyday life”. These individuals were excluded from the respective data analysis. We found substantial evidence for the absence of a group difference regarding the expected training gains between the WM group (M = 5.44, SD = 1.30) and the VS group (M = 5.47, SD = 1.87), BF_{H0} = 5.51 ± 0.00%. Regarding expected transfer to untrained tasks, we found decisive evidence for participants in the WM group (M = 4.20, SD = 1.66) reporting higher levels in expected cognitive transfer than the VS group (M = 3.15, SD = 1.51), BF_{H1} > 100 ± 0.00%. Finally, we found ambiguous evidence for the absence of a difference in expected transfer to everyday life between the WM group (M = 4.59, SD = 1.76) and the VS group (M = 4.25, SD = 1.73), BF_{H0} = 2.97 ± 0.00% (see Table B8 in the Appendix B for NHST results).

5.5. Discussion

The goal of the study was to investigate the evidence for and against the effectiveness of WM training in eliciting generalized performance improvements in older adults using Bayesian statistics. To this aim, we investigated the training, near, and far transfer effects after a WM training intervention in a fairly large sample of 142 healthy older adults. To overcome frequent methodological issues in the cognitive training field, we conducted a randomized-controlled, double-blind trial using an active, adaptive VS control condition. Further, training and transfer effects to WM, fluid intelligence, shifting, and inhibition were assessed on the level of abilities, that is, using multiple cognitive tasks as indicators for the construct of interest.

Consistent with previous literature (Karbach & Verhaeghen, 2014; Melby-Lervåg et al., 2016), we found that WM training yielded substantial practice effects across the 25 sessions of training in the respective WM tasks. Moreover, the WM training group also showed large improvements from pre- to postassessment in the criterion tasks when compared with the VS control group. Although participants substantially improved in the trained tasks, we found substantial evidence against near transfer effects to structurally dissimilar WM tasks, and substantial to strong evidence against far transfer effects to fluid intelligence, shifting, and inhibition on the ability level. Thus, our results do not support the notion of generalized enhancements in cognitive functioning after intensive, computer-based WM training in older adults.

5.5.1. Absence of Transfer

At first, the absence of transfer in our study may seem contradictory to past research, as many studies reported at least near transfer in older adults (see Karbach & Verhaeghen, 2014 for a meta-analysis). However, our data consistently supported the absence of near transfer to structurally different WM tasks and far transfer effects to fluid intelligence, shifting, and inhibition (BFs from 5.26 to 11.11), which is in line with recent WM training studies with larger samples of younger adults (De Simoni & von Bastian, under revision; Sprenger et al., 2013). This finding is especially striking, as participants in the WM training group reported higher posttraining expectations regarding their improvements on the cognitive transfer tasks. There are multiple possible explanations for the absence of transfer effects found in this study.

First, the absence of near transfer to structurally dissimilar WM tasks indicates that the training intervention did not change WMC. One possible reason is that the training intervention was not intensive enough to change WMC and subsequently produce substantial transfer effects (e.g., see Schmiedek, Lövdén, & Lindenberger, 2010 for a high-intensity training intervention successfully producing positive transfer even in old age). Another possible reason is though that the training intervention facilitated the acquisition of task-specific processes that are relevant to perform the tasks efficiently and thus improve performance. Although we included three relatively distinct WM training tasks to enhance variability in learning, a factor that had been suggested to enhance generalizability of practice (Schmidt & Bjork, 1992), practicing the same set of tasks with the same set of stimuli for 25 sessions may have still encouraged the acquisition of strategies tied to the stimuli sets or the structure of the tasks, thus hindering the generalization of improvements to tasks with different stimuli and surface structure (cf. Lustig, Shah, Seidler, & Reuter-Lorenz, 2009). This is in line with some recent meta-analyses suggesting that training interventions with lower intensity (i.e., fewer or less frequent sessions) are more likely to produce transfer effects (Lampit et al., 2014; but see Melby-Lervåg et al., 2016). In addition to task-specific processes, the improvements observed during training and in the criterion tasks may also reflect individuals' capacity to adapt to the training setting and the increase in confidence when performing the computer-based cognitive tasks. Although all of our older participants were experienced in using a computer, they were probably not familiar with practicing such relatively complex WM tasks. Thus, it is possible that the performance increases in the trained tasks primarily reflect improved task literacy.

Second, it is possible that WM training is effective only under certain circumstances and for some individuals. For example, some meta-analyses suggest home-based individual training interventions to be less effective than lab-based group training (Lampit et al., 2014, but see Kelly et al., 2014), as the latter included face-to-face supervision by a trainer to guarantee compliance and prevent cheating, provision of motivational and IT support, and nonspecific effects of social interaction. Although we cannot completely exclude that these training-related aspects may have limited the effectiveness of our training intervention, we minimized these issues by maximizing personal contact throughout the study (e.g., IT support, weekly motivational quotes, and daily and weekly feedback on training progress). Further, we ensured compliance using Tatool Online and contacted participants if they fell behind their schedule, possibly contributing to the fact that only two participants dropped out during the training intervention.

Further, individual differences factors such as personality, training-related beliefs, and motivation can influence training gains and transfer effects (see Katz et al., 2016 for an overview, but see Guye et al., 2017). As the heterogeneity between older individuals might be relatively large, this may potentially mask transfer effects on the group level, if they are assumed to be relatively small (cf. Bürki et al., 2014). To gain insight into whether subgroups of individuals benefited more from the intervention than others, we analyzed the training data of this study and investigated whether 29 individual-differences variables reported frequently in the literature (including demographic variables, real-world cognition, motivation, training-related beliefs or personality traits) predicted change in training performance (Guye et al., 2017). However, out of all of these investigated variables, only one predicted change in training performance in the older adults (i.e., belief in the malleability of intelligence; Dweck, 2000), and it did so opposite to common expectations (i.e., participants believing more strongly in intelligence being fixed showed larger training gains). These results suggest that the role of individual differences in explaining variance in training gains is negligible only. Assuming that transfer gains are a consequence of training gains, our findings thus render it unlikely that individual differences in these commonly proposed traits can explain the (in-)effectiveness of cognitive training interventions.

Third, it is possible that WM training effects did not generalize simply because repetitive cognitive task practice is not effective in eliciting changes in WM capacity in general. Hence, the near and far transfer effects reported in recent meta-analyses (e.g., Karbach & Verhaeghen, 2014) might have been substantially overestimated due to methodological limitations of the (included) studies (i.e., small sample sizes, passive control groups, transfer assessment on the level of individual tasks). Furthermore, these effects may have been aggravated by more general problems in psychology such as publication bias. For example, notoriously small sample sizes, in particular in studies with older adults, yielding low statistical power seriously threats statistical inferences by increasing the probability of inflated effect sizes (cf. Bogg & Lasecki, 2015; Halsey et al., 2015). Hence, meta-analyses based on these inflated effect sizes potentially overestimate the effect of training interventions.

5.5.2. Limitations and Future Research

One limitation of our study is that computer-based cognitive training interventions generally attract highly educated and computer-versed older adults who have an inherent interest in their cognition and in ways to improve their cognitive functioning. This self-selection bias towards a highly functioning sample can cause a threat to the generalizability of our results to the general population of older adults. Participants in our sample were considerably more educated than the general population in Switzerland. In our sample, 53 % of the 65-74 years old and 48 % of the 75-80 years old graduated from an institution for higher education (i.e., tertiary institution), whereas only about 14 % of the 65-74 years old and 10 % of the 75-80 years old hold such a qualification in the general population (Bundesamt für Statistik, 2016). Such high levels of cognitive functioning in older participants may leave less room for improvements in cognitive tasks and so could have limited the likelihood to observe transfer effects. Similarly, all participants in our sample had to have access to a computer including Internet connection at home to be able to receive the training intervention. This is, however, not the standard situation in the general population in Switzerland in which only about 50% of individuals older than 65 own a computer or laptop (Seifert & Schelling, 2015). Both of these factors may reduce the generalization of our results. Thus, future research should aim to investigate training effectiveness in more representative samples.

A second limitation is that traditional lab-based cognitive tasks (such as those used in our study) capture an individuals' cognitive performance, that is, when they expend their maximum effort. However, an equally important aspect of an individuals' cognitive capacity is how individuals perform during everyday life activities in their natural environment (cf. Verhaeghen et al., 2012). Developing training interventions that target everyday life cognition and include activity-based transfer measures could increase not only the ecological validity of cognitive training but also boost its effectiveness (cf. Guye et al., 2016).

5.6. Conclusion

Whether WM training interventions can enhance general cognitive functioning is heatedly debated. In line with accumulating evidence speaking against its effectiveness in younger adults (cf. Dougherty et al., 2016), and despite decisive evidence for substantial improvements on the trained WM tasks, we found substantial evidence for the absence of near transfer to WM and substantial to strong evidence for the absence of far transfer to fluid intelligence, shifting, and inhibition. Our results thus suggest that WM training is no "quick-fix solution" to improve general cognitive functioning in older adults.

5.7. APPENDIX B

SUPPLEMENTAL MATERIALS

Table B1

Participant Demographics

	Group		
Demographics	WM	VS	*p*
Gender (f/m)	29 / 39	39 / 35	.303
Age (years)	70.15 (3.57)	70.53 (3.75)	.537
Education [a]	4.47 (1.77)	3.96 (1.67)	.079
MMSE score	29.16 (0.78)	29.28 (0.93)	.398
GDS score	0.68 (1.09)	0.64 (0.87)	.804

Note. Means and standard deviations in parentheses. *P*-values indicate that the two groups did not differ significantly as in their basic demographics as determined by two-tailed independent *t*-tests (Chi-Square test in the case of gender). WM = working memory; VS = visual search; MMSE = Mini-Mental State Examination; GDS = Geriatric Depression Scale.

[a] The scale for education ranged from 0 (no formal education) to 7 (doctorate)

Table B2

Correlations and Reliabilities of the Cognitive Tasks

Task	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Criterion CS	.90																				
2. Criterion binding	**.41**	.59																			
3. Criterion updating	**.48**	**.25**	.87																		
4. WM BP	**.30**	**.44**	**.29**	.74																	
5. WM binding	**.26**	**.20**	**.29**	**.28**	.52																
6. WM updating	**.37**	**.51**	**.46**	**.50**	**.21**	.93															
7. Circles	.11	**.17**	**.17**	**.19**	.12	**.18**	.81														
8. Crosses	-.06	.12	-.04	.10	.04	.15	**.25**	.94													
9. Rectangles	.05	**.19**	.12	.16	-.04	**.21**	**.34**	**.24**	.93												
10. RAPM	**.24**	**.19**	**.25**	.11	.15	**.26**	.00	-.07	.13	.45											
11. Locations	.15	.11	**.21**	.10	.07	**.24**	.05	.05	.11	.00	.54										
12. Relationships	**.28**	**.27**	**.31**	.14	.08	**.38**	.08	-.03	**.17**	**.35**	**.22**	.71									
13. SC categorical	-.08	-.16	-.09	**-.19**	.03	-.14	-.06	.02	-.04	-.09	.07	-.16	.83								
14. SC figural	.06	.04	-.03	-.10	.05	-.09	-.01	-.02	-.06	-.03	-.06	-.15	**.31**	.82							
15. SC numerical	-.16	-.16	**-.27**	-.15	-.05	**-.22**	-.01	.01	-.14	-.14	.06	**-.21**	**.30**	**.50**	.94						
16. MC categorical	.09	-.11	.10	-.06	-.02	-.03	-.09	-.06	-.03	.04	.06	-.02	-.02	.05	**.24**	.97					
17. MC figural	-.06	**-.27**	-.10	**-.17**	-.02	-.13	**-.19**	-.10	-.14	**-.17**	-.12	-.06	.02	-.06	.08	**.36**	.97				
18. MC numerical	.07	.14	**.20**	-.04	-.08	.04	-.03	.06	.12	.07	.00	**.25**	**-.20**	-.16	**-.20**	**.17**	.08	.97			
19. Flanker	.16	**.17**	**.19**	**.18**	.08	.09	.12	.09	.09	.07	.15	**.20**	-.11	-.01	-.10	.03	.02	.13	.80		
20. Stroop	.01	.04	.12	.05	.-01	.06	-.05	-.05	-.07	.06	.09	-.07	-.02	-.01	.07	.11	-.06	.00	.00	.91	
21. Simon	.06	.14	.11	-.03	.14	.04	.08	.08	-.01	.04	.07	.07	.08	.12	.08	.11	.00	-.08	-.03	.11	.73

Note. Correlation coefficients and reliabilities (on the diagonal) for single tasks. Bold values represent significant Pearson correlations ($p < .05$). Reliabilities were computed using split-half reliability corrected with the Spearman-Brown's prophecy formula for the shifting tasks (switch costs categorical, switch costs figural, switch costs numerical, mixing costs categorical, mixing costs figural, mixing costs numerical) and the inhibition tasks (Stroop, Flanker, Simon), and using Cronbach's alpha for all other tasks. CS = complex span; BP = Brown-Peterson; RAPM = Raven Advanced Progressive Matrices; SC = switch costs, MC = mixing costs.

Table B3

Group Comparisons of the Number of Completed Training Sessions

	Group				
	WM	VS	*t*	*df*	*p*
Number of training sessions	24.97 (0.71)	24.88 (0.95)	0.66	134.66	.512

Note. Means and standard deviations in parentheses. The *p*-value indicates that the two groups did not differ significantly as in the number of completed training sessions as determined by a two-tailed independent *t*-test. WM = working memory; VS = visual search.

Table B4

Effect of Session on Training Performance for Each Training Task

Task	Fixed effect	*b*	*SE*	*t*	*df*	*p*
		Working Memory				
Complex span	Intercept	3.63	0.08	44.10	67.01	**<.001**
	Session	0.07	0.00	47.82	1624.09	**<.001**
Binding	Intercept	4.50	0.07	62.53	67.01	**<.001**
	Session	0.09	0.00	59.09	1624.10	**<.001**
Memory updating	Intercept	3.22	0.08	42.60	67.00	**<.001**
	Session	0.04	0.00	37.67	1624.05	**<.001**
		Visual Search				
Circles	Intercept	35.82	0.72	50.08	73.00	**<.001**
	Session	1.35	0.01	107.88	1762.22	**<.001**
Rectangles	Intercept	39.77	0.43	92.32	72.89	**<.001**
	Session	1.52	0.01	116.63	1762.54	**<.001**
Crosses	Intercept	36.71	0.67	54.46	73.00	**<.001**
	Session	1.39	0.01	108.80	1762.25	**<.001**

Note. Session was included in the linear mixed effects models as linear contrast. Bold *p*-values indicate significant effects.

Table B5

Baseline Differences in Cognitive Abilities

Ability	Fixed effect	*b*	*SE*	*t*	*df*	*p*
Criterion	Intercept	-0.10	0.09	1.11	140.00	.268
	Group	0.21	0.13	1.61	140.00	.110
Visual search	Intercept	0.01	0.08	0.17	140.00	.865
	Group	-0.03	0.12	0.25	140.00	.806
Working memory	Intercept	-0.13	0.09	1.47	140.00	.144
	Group	0.26	0.12	2.12	140.00	**.035**
Fluid intelligence	Intercept	-0.05	0.08	0.67	140.00	.505
	Group	0.11	0.11	0.96	140.00	.336
Shifting SC	Intercept	0.14	0.09	1.61	140.00	.110
	Group	-0.29	0.13	2.33	140.00	**.021**
Shifting MC	Intercept	-0.03	0.08	0.34	140.00	.731
	Group	0.06	0.12	0.50	140.00	.619
Inhibition	Intercept	-0.02	0.07	0.28	140.21	.783
	Group	0.04	0.10	0.40	139.78	.690

Note. Estimates are based on standardized data. Group differences were assessed by linear mixed effects models. Bold *p*-values indicate significant effects. SC = switch costs; MC = mixing costs.

Table B6

Descriptive Statistics and Group Differences of Cognitive Task Performance at Pre- and Postassessment

	Preassessment		BFs			NHST			Postassessment		BFs			NHST		
Task	WM	VS	BF_{H0}	BF_{H1}	Error	*t*	*df*	*p*	WM	VS	BF_{H0}	BF_{H1}	Error	*t*	*df*	*p*
Criterion																
Complex span	0.31 (0.18)	0.26 (0.16)	1.54	0.65	0.00	1.67	135.03	.097	0.73 (0.16)	0.30 (0.19)	<0.01	**>100**	-	14.88	139.64	**<.001**
Binding	1.06 (0.65)	0.98 (0.58)	**4.21**	0.24	0.00	0.77	135.17	.441	1.29 (0.65)	1.10 (0.57)	<0.01	**>100**	0.00	1.86	133.53	**.033**
Memory updating	0.41 (0.17)	0.37 (0.15)	2.34	0.43	0.00	1.37	135.87	.173	0.65 (0.12)	0.46 (0.16)	<0.01	**>100**	-	7.72	135.44	**<.001**
Visual search																
Circles	0.96 (0.08)	0.95 (0.09)	**3.90**	0.26	0.00	0.88	139.80	.380	0.96 (0.09)	0.99 (0.02)	<0.01	**>100**	0.00	2.64	71.97	**.005**
Crosses	0.83 (0.23)	0.89 (0.19)	1.79	0.56	0.00	1.56	129.46	.121	0.88 (0.20)	0.99 (0.02)	<0.01	**>100**	0.00	4.60	67.92	**<.001**
Rectangles	0.91 (0.17)	0.91 (0.18)	**5.49**	0.18	0.00	0.16	139.97	.876	0.90 (0.19)	0.98 (0.06)	<0.01	**>100**	0.00	3.54	81.25	**.001**
Working memory																
Brown-Peterson	0.35 (0.14)	0.31 (0.15)	1.64	0.61	0.00	1.64	139.87	.103	0.42 (0.15)	0.36 (0.16)	<0.01	**>100**	0.00	2.18	139.58	**.016**
Binding	1.12 (0.67)	0.99 (0.55)	2.59	0.39	0.00	1.28	129.44	.202	1.52 (0.61)	1.27 (0.52)	<0.01	**>100**	0.00	2.60	131.92	**.005**
Memory updating	0.33 (0.17)	0.28 (0.15)	1.32	0.76	0.00	1.77	134.99	.079	0.38 (0.16)	0.32 (0.18)	<0.01	**>100**	0.00	2.10	139.63	**.019**
Fluid Intelligence																
RAPM	0.41 (0.16)	0.37 (0.16)	2.41	0.42	0.00	1.35	139.34	.178	0.48 (0.20)	0.41 (0.18)	<0.01	**>100**	0.00	2.00	134.31	**.024**
Relationships	0.43 (0.16)	0.42 (0.13)	**4.32**	0.23	0.00	0.73	129.90	.465	0.47 (0.16)	0.44 (0.15)	0.02	**49.42**	0.00	0.99	138.03	.162
Locations	0.26 (0.12)	0.26 (0.11)	**5.51**	0.18	0.00	0.13	137.66	.900	0.33 (0.14)	0.33 (0.12)	0.20	**4.97**	0.00	0.05	130.84	.481
Shifting SC																
Categorical	-0.27 (0.16)	-0.20 (0.12)	0.10	**9.90**	0.00	2.95	122.80	**.004**	-0.26 (0.14)	-0.23 (0.14)	0.06	**15.82**	0.00	1.61	138.99	.054
Figural	-0.22 (0.13)	-0.18 (0.15)	1.80	0.56	0.00	1.58	139.59	.116	-0.23 (0.12)	-0.20 (0.13)	0.15	**6.61**	0.01	1.33	139.88	.092
Numerical	-0.27 (0.26)	-0.24 (0.26)	**4.25**	0.24	0.00	0.76	139.01	.447	-0.28 (0.19)	-0.26 (0.24)	1.42	0.70	0.02	0.58	136.38	.283
Shifting MC																
Categorical	-0.56 (0.22)	-0.59 (0.23)	**3.95**	0.25	0.00	0.86	139.55	.390	-0.50 (0.17)	-0.55 (0.16)	<0.01	**>100**	0.00	1.65	136.43	.051
Figural	-0.68 (0.22)	-0.70 (0.23)	**5.00**	0.20	0.00	0.48	139.93	.635	-0.68 (0.18)	-0.69 (0.19)	**9.97**	0.10	0.03	0.26	139.87	.397
Numerical	-0.54 (0.28)	-0.53 (0.24)	**5.31**	0.19	0.00	0.31	134.16	.758	-0.48 (0.22)	-0.55 (0.24)	<0.01	**>100**	0.00	1.79	139.98	**.038**
Inhibition																
Flanker	-0.03 (0.05)	-0.03 (0.04)	**5.52**	0.18	0.00	0.07	132.56	.941	-0.03 (0.11)	-0.02 (0.04)	0.94	1.06	0.00	0.66	82.16	.254
Stroop	-0.19 (0.11)	-0.19 (0.13)	**5.44**	0.18	0.00	0.21	138.47	.833	-0.18 (0.10)	-0.19 (0.12)	0.02	**49.59**	0.00	1.00	138.05	.159
Simon	-0.05 (0.02)	-0.05 (0.03)	**5.10**	0.20	0.00	0.43	139.11	.665	-0.04 (0.02)	-0.04 (0.02)	0.04	**27.44**	0.00	0.72	138.85	.235

Note. Means and standard deviations in parentheses. All values are accuracy proportions, except for shifting (proportional switch costs and mixing costs), binding (*d'*), and inhibition (proportional interference). Bayes factors for pre-assessment scores were determined by Bayesian two-tailed independent *t*-tests; Bayes factors for post-assessment were determined by Bayesian one-tailed *t*-tests to test the a priori hypothesis working memory group > visual search group; bold Bayes factors values indicate at least substantial evidence for the presence or absence of group differences.

Bold *p*-values indicate a significant group difference, as determined by two-tailed independent *t*-test for pre-assessment and one-tailed independent *t*-test for post assessment. WM = working memory; VS = visual search; BF = Bayes factor; H_0 = null hypothesis; H_1 = alternative hypothesis; RAPM = Raven Advanced Progressive Matrices; SC = switch costs; MC = mixing costs.

Table B7

Group Differences in Gain Scores

Ability	Fixed effect	*b*	*SE*	*t*	*df*	*p*
Criterion	Intercept	0.32	0.31	1.02	2.09	.412
	Group	1.15	0.10	11.89	422.00	**< .001**
Visual search	Intercept	0.47	0.10	4.94	13.52	**< .001**
	Group	-0.43	0.13	3.22	140.00	**.002**
Working memory	Intercept	0.28	0.09	3.18	2.22	.063
	Group	0.10	0.10	0.94	140.00	.075
Fluid intelligence	Intercept	0.34	0.12	2.83	3.35	.058
	Group	0.08	0.11	0.74	140.00	.463
Shifting SC	Intercept	-0.12	0.07	1.63	140.00	.106
	Group	0.11	0.10	1.10	140.00	.272
Shifting MC	Intercept	0.06	0.08	0.69	10.32	.507
	Group	0.11	0.11	1.01	140.00	.313
Inhibition	Intercept	0.10	0.08	1.14	140.33	.257
	Group	-0.02	0.12	0.14	139.91	.891

Note. Group differences were assessed by linear mixed effects models. Bold *p*-values indicate significant effects. SC = switch costs; MC = mixing costs.

Table B8

Group Differences in Training-Related Expectations

	Group				
Expectations	WM	VS	*t*	*df*	*p*
Training gains	5.44 (1.30)	5.47 (1.87)	0.12	130.36	.906
Cognitive transfer	4.20 (1.66)	3.15 (1.51)	3.86	131.66	**< .001**
Transfer to everyday life	4.59 (1.76)	4.25 (1.73)	1.16	135.01	.248

Note. Mean values and standard deviations in parentheses. Group differences were assessed by two-tailed independent *t*-tests. Bold *p*-values indicate significant effects. WM = working memory; VS = visual search.

ARTICLE IV

6 DO INDIVIDUAL DIFFERENCES PREDICT CHANGE IN TRAINING PERFORMANCE? A LATENT GROWTH CURVE MODELING APPROACH

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Written informed consent was obtained from all participants. Both studies were approved by the ethics committee of the Department of Psychology of the University of Zurich.

6.1. ABSTRACT

Cognitive training interventions have become increasingly popular as a potential means to cost-efficiently stabilize or enhance cognitive functioning across the lifespan. Large training improvements have been consistently reported on the group level, with, however, large differences on the individual level. Identifying the factors contributing to these individual differences could allow for developing individually tailored interventions to boost training gains. In this study, we therefore examined a range of individual differences variables that had been discussed in the literature to potentially predict training performance. To estimate and predict individual differences in the training trajectories, we applied Latent Growth Curve models to existing data from three working memory training interventions with younger and older adults. However, we found that individual differences in demographic variables, real-world cognition, motivation, cognition-related beliefs, personality, leisure activities, and computer literacy and training experience were largely unrelated to change in training performance. Solely baseline cognitive performance was substantially related to change in training performance and particularly so in young adults, with individuals with higher baseline performance showing the largest gains. Thus, our results conform to magnification accounts of cognitive change.

Keywords: working memory training, individual differences, latent growth curve modeling

6.2. INTRODUCTION

Over the past decade, there has been an exploding interest in computer-based commercial "brain training" programs and in scientific evidence relating to the effectiveness of such interventions, triggered by promising results of working memory (WM) training gains generalizing to previously untrained cognitive abilities such as intelligence in both younger (e.g., Jaeggi et al., 2008) and older adults (e.g., Borella et al., 2010). Although the idea of improving general cognitive functioning within a few weeks is enticing, there is also accumulating evidence against a generalized effect of WM training (e.g., Clark, Lawlor-Savage, & Goghari, 2017; De Simoni & von Bastian, under revision; Guye & von Bastian, 2017; Sprenger et al., 2013). Even on the meta-analytic level, evidence is mixed regarding the effectiveness of cognitive training in both younger and older adults (e.g., Au et al., 2015; Dougherty et al., 2016; Karbach & Verhaeghen, 2014; Kelly et al., 2014; Lampit et al., 2014; Melby-Lervåg & Hulme, 2013; Melby-Lervåg et al., 2016; Schwaighofer et al., 2015; Soveri et al., 2017). Aside from design and methodological choices potentially explaining the diverging findings (e.g., Noack et al., 2009; Shipstead et al., 2012), many authors increasingly articulated the potentially important influence of individual differences on cognitive training trajectories and outcomes (e.g., Buitenweg, Murre, & Ridderinkhof, 2012; Guye et al., 2016; Könen & Karbach, 2015; Shah, Buschkuehl, Jaeggi, & Jonides, 2012; von Bastian & Oberauer, 2014).

Individual differences in cognitive functioning (e.g., Ackerman & Lohman, 2006) and learning potential (e.g., Stern, 2017) accentuate with increasing age (e.g., Rabbitt, Diggle, Holland, & McInnes, 2004), and have been shown to be related to personality (e.g., Graham & Lachman, 2012), cognition-related beliefs such as need for cognition (NFC; e.g., Fleischhauer et al., 2010; Hill et al., 2013), and everyday life activities (e.g., Jopp & Hertzog, 2007). Investigating which of these individual differences potentially predict cognitive training outcomes may not only explain inconsistencies concerning the effectiveness of cognitive training, but also identify possible subgroups of individuals that are more or less responsive to cognitive training, thereby constituting the conceptual groundwork for developing individually-tailored interventions to boost training effectiveness.

6.2.1. PREDICTORS OF COGNITIVE TRAINING OUTCOMES

As yet, only few studies have examined how individual differences are associated with cognitive training outcomes (see Katz et al., 2016 for an overview), with most existing studies relating training outcomes to demographic variables (e.g., age), baseline cognitive performance, motivation, cognition-related beliefs (e.g., theories of intelligence), and personality traits (e.g., neuroticism and conscientiousness).

So far, the effect of age on training outcomes has received the most attention. Age-comparative studies mostly reported larger training effects in younger than in older adults (e.g., Brehmer, Westerberg, & Bäckman, 2012; Bürki et al., 2014; Schmiedek et al., 2010; von Bastian, Langer, et al., 2013), and in young-old adults compared to old-old adults (e.g., Borella et al., 2014; Zinke et al., 2014).

These results are in line with the notion of a magnification effect (also known as amplification or Mattew effect; Kliegl, Smith, & Baltes, 1990; Lövdén, Brehmer, Li, & Lindenberger, 2012; Verhaeghen & Marcoen, 1996), suggesting that younger individuals benefit more from cognitive training, as they have the additional cognitive resources available required for successfully completing the training tasks. However, other studies found that children and older adults benefited more from training than young adults (e.g., Bherer et al., 2008; Karbach & Kray, 2009). Such compensation effects have been argued to emerge as participants with lower initial cognitive status have more room for improvement (see Titz & Karbach, 2014 for a review). These diverging findings are reflected by recent meta-analyses, with some reporting evidence for age being a moderator of training outcomes (e.g., Melby-Lervåg & Hulme, 2013) and others not (e.g., Karbach & Verhaeghen, 2014; Schwaighofer et al., 2015). A closely related, yet potentially distinct factor possibly contributing to these mixed findings is general cognitive functioning (von Bastian & Oberauer, 2014). Only few studies have directly assessed the effect of baseline cognitive performance on training outcomes though, with some evidence suggesting that initially low-performing individuals benefit more from training (e.g., Jaeggi et al., 2008; Zinke et al., 2014) but others reported opposite effects (e.g., Bürki et al., 2014).

Although motivation is arguably one of the most plausible factors possibly influencing cognitive training outcomes, its association with training performance has not yet been comprehensively examined. One exception is a study by Brose et al. (2012), who reported a positive association between daily motivation and daily cognitive performance on a 3-back task, indicating that on days on which task-related motivation was lower than on average, daily cognitive performance was also reduced. Some studies have investigated the effect of related concepts, including cognition-related beliefs such as individuals' beliefs about the malleability of intelligence (theories of intelligence; Dweck, 2000). For instance, Jaeggi, Buschkuehl, Shah and Jonides (2014) found that, irrespective of training intervention (control or experimental intervention), the group of individuals indicating high beliefs in the malleability of intelligence (a "growth mindset") showed larger transfer effects than the group of individuals who believed that intelligence cannot be changed (but see Thompson et al., 2013). Due to the fact that the groups were determined by median split, these results should, however, be interpreted with caution, as median split and extreme group analyses can potentially inflate the effect sizes and consequently overestimate the importance of a given effect (Moreau et al., 2016; Unsworth et al., 2015). Indeed, other studies have not found an association of cognition-related beliefs with training outcomes (Minear et al., 2016; Sprenger et al., 2013).

Finally, there is some evidence for personality traits being related to training outcomes. It has been reported that conscientiousness is positively related to training performance, but negatively to far transfer effects (Studer-Luethi et al., 2012). Further, neuroticism has been found to be negatively associated with mean training performance (but not training gain; Studer-Luethi et al., 2012; 2016) and transfer effects (Studer-Luethi et al., 2012; 2016, see also Urbánek & Marček, 2015 for similar results using the Personality System Interaction personality factors), except when training task complexity is low (Studer-Luethi et al., 2012).

In sum, there is some tentative evidence that individual differences may predict training performance and transfer effects. Studies attempting to estimate the role of individual differences based on sufficiently large training samples and continuous predictors are, however, scarce. Further, some individual differences have been entirely neglected, including cognitive performance in real-world context (e.g., education), training-related leisure activities (e.g., gaming), and computer literacy or previous training experience.

6.2.2. THE PRESENT STUDY

The goal of this study was to enhance the understanding of who benefits from cognitive training and who does not. Using Latent Growth Curve (LGC) modeling, we therefore examined (1) the individual cognitive training trajectories, (2) the association of baseline cognitive performance with change in training performance, and (3) which individual differences predicted change in training performance.

We reanalyzed three data sets obtained from two randomized-controlled, double-blind WM training studies investigating two WM interventions in younger (De Simoni & von Bastian, under revision) and one in older adults (Guye & von Bastian, 2017). Observed improvements in the trained tasks were substantial in size and in line with numerous studies consistently reporting training effects across a wide variety of training regimes and trained abilities (e.g., Karbach & Verhaeghen, 2014). The two training studies were similar regarding the included questionnaires assessing individual differences potentially predicting training performance, and the training regimen itself (i.e., trained tasks, training duration, frequency, adaptive task difficulty, and nature of the control group). In the first study (De Simoni & von Bastian, under revision), younger adults received either of two single-paradigm WM training interventions (i.e., memory updating and binding training). In the second study (Guye & von Bastian, 2017), older adults received a mixed-paradigm WM training intervention, consisting of a memory updating, a binding, and a complex span task. All three interventions were adaptive, with the level of difficulty increasing depending on individuals' performance.

To estimate the training trajectories, we fitted LGC models to the data recorded during training. LGC modeling uses structural equation modeling (SEM) to estimate interindividual differences in intraindividual change over time. LGC modeling is highly flexible as it can handle a variety of methodological issues typically occurring in training research such as partially missing data, non-normally distributed data, or non-linear change trajectories (Curran, Obeidat, & Losardo, 2010). Further, LGC modeling has the advantage to account for measurement error and to provide separate latent estimates for baseline cognitive performance (i.e., the intercept) and change in training performance (i.e., the slope). The distinction between the two latent factors allows for estimating how baseline cognitive performance is related to change in performance, with a positive relationship reflecting magnification, and a negative relationship reflecting compensation effects. Further, to investigate how the individual differences variables are associated with the intercept and the slope, we extended the LGC models by predicting the variance in baseline cognitive performance and, more importantly, change in training performance by (1) demographic variables, (2) real-world cognition, (3) motivation, (4) cognition-related beliefs, (5) personality, (6) leisure activities, and (7) computer literacy and training experience.

Statistical evidence for the predictive value of baseline cognitive performance and each of the individual differences variables was evaluated using Bayes factors (BF). The BF is a statistical index ranging from 0 to infinity and quantifies the strength of evidence for one hypothesis (usually the alternative hypothesis H_1, postulating the presence of an association) compared to another hypothesis (usually the null hypothesis H_0, postulating the absence of an association). Hence, BFs allow for evaluating the strength evidence not only for the presence of an association, but explicitly also for the absence of a proposed association. Accordingly, using BFs has become increasingly popular in the area of cognitive enhancement (e.g., Antón et al., 2014; Clark et al., 2017; De Simoni & von Bastian, under revision; Guye & von Bastian, 2017; Kirk, Fiala, Scott-Brown, & Kempe, 2014; Paap, Johnson, & Sawi, 2014; Sprenger et al., 2013; von Bastian et al., in press; von Bastian & Oberauer, 2013).

Based on previous findings, we expected positive associations of motivation (Brose et al., 2012), a growth mindset (Jaeggi et al., 2014), and conscientiousness (Studer-Luethi et al., 2012) with change in training performance. Regarding neuroticism, our expectations were less specific, given that previous literature reported evidence for a negative association of neuroticism with mean training performance and transfer effects, but not with training gains (e.g., Studer-Luethi et al., 2012; 2016). Based on the results by Bürki et al. (2014), methodologically the most similar study to our own, we expected a negative association of age and a positive association of baseline cognitive performance with change in cognitive performance, which would support the magnification hypothesis. For all the other individual differences variables, the analyses were exploratory.

6.3. METHOD

Detailed methods regarding the training interventions have been reported previously (De Simoni & von Bastian, under revision; Guye & von Bastian, 2017). In the following, we summarize the key characteristics of each study's methodology with a focus on the individual differences measures.

6.3.1. PARTICIPANTS

The final sample sizes ranged from 58 to 68 (see Table 9 for detailed sample description). The Young-Updating and Young-Binding samples were drawn from a study of healthy younger participants aged between 18 – 36 years, and the Old-Mixed sample was drawn from a study of healthy older participants aged between 65 – 80 years. Younger participants were recruited through the participant pool of the Department of Psychology of the University of Zurich, postings at the university campus, and short study presentations during lectures. Older participants were recruited through the participant pool of the University Research Priority Program "Dynamics of Healthy Aging", lectures at the Senior Citizens' University of Zurich, flyers, online announcements, and word-of-mouth. All participants were fluent or native German speakers and had a computer with Internet connection at home. Written informed consent was obtained from all participants. Both studies were approved by the ethics committee of the Department of Psychology of the University of Zurich. After study completion, younger participants received either CHF 120 (approx. USD 120) or CHF 20 (USD 20) plus 10 course credits, moreover, they could earn a bonus up to a maximum of 50 CHF (USD 50), depending on the level of difficulty that they reached during training. Older participants received CHF 150 (approx. USD 150).

Younger participants reported no current psychiatric or neurological disorders, psychotropic drug use, or color blindness. Older participants also reported no current psychiatric or neurological disorders, psychotropic drug use, and no significant motor, hearing or vision impairments. Further, they were screened for color blindness (Ishihara, 1917), subclinical depression (GDS; Sheikh & Yesavage, 1986: cut-off criterion = 4), and cognitive impairment (MMSE; Folstein, Folstein, & McHugh, 1975: cut-off criterion = 26).

Table 9

Demographics of Study Participants

	Sample		
Demographics	Young-Updating	Young-Binding	Old-Mixed
Sample size (*n*)	58	64	68
Intervention	Memory updating	Binding	Mixed-paradigm
Age	22.57 (2.99)	24.77 (4.03)	70.40 (3.72)
Gender (f/m)	39/19	45/19	30/38
Education [a]	5 (0.00)	5 (0.00)	5 (1.48)
MMSE score	-	-	29.21 (0.76)
GDS score	-	-	0.65 (1.02)

Note. Values are means and standard deviations in parentheses (median and median absolute deviation in parentheses for education).

[a] The scale for education ranged from 0 (no formal education) to 7 (doctorate).

6.3.2. Studies and Material

Cognitive Training Interventions

Training procedures were identical for the three samples if not mentioned otherwise. Tatool was used to deliver the self-administered training interventions at home and to monitor participants' training compliance (von Bastian, Locher, et al., 2013). The default adaptive score and level handler implemented in Tatool was used to adjust task difficulty to participants' performance throughout the training phase. Both the set size (i.e., number of memoranda) and the response time limit varied depending on the level of task difficulty (see below). Younger participants completed 20 sessions of WM training (30-45 minutes per session) within five weeks. Each training session consisted of 12 trials per task in the Young-Updating sample and 24 trials per task in the Young-Binding sample. Interventions comprised verbal, spatial, visual, and numerical memory updating tasks (Young-Updating sample) and verbal, spatial, visual, and numerical binding tasks (Young-Binding sample). Both younger samples trained each task for a maximum of 11.25 min per session. Older participants completed 25 sessions of WM training (30-45 minutes per session) within five weeks, with the intervention consisting of a complex span, a binding, and a memory updating task each of which contained visuo-spatial memoranda. Each task was trained for a maximum of 15 min per session, with each session consisting of 15 trials per task. Set size achieved at the end of each session and task was used as the dependent variable. Table 10 lists an overview of the training tasks.

UPDATING TRAINING. The Young-Updating sample practiced four memory updating tasks (adapted from Lewandowsky, Oberauer, Yang, & Ecker, 2010). In these tasks, participants had to memorize a set of stimuli presented simultaneously for 500 ms per item. In the subsequent updating phase, participants had to transform individual memoranda (e.g., mentally rotate previously memorized arrows or applying a simple arithmetic operation to a number), enter the result of the transformation, and remember that result of the transformation. In half of the trials, a cue presented for 500 ms indicated which of the memorandum had to be updated. After nine updating steps, participants had to recall the most recent result of each stimulus. Task difficulty was adjusted to individual performance by increasing the set size (i.e., number of simultaneously presented memoranda) and reducing the time limit to respond to the updating prompts.

Table 10

Working Memory Training Tasks of the Training Interventions

Task (-version)	Description
Memory updating training	
Arrows	Memorize a set of arrows and update by rotating them for 45 degrees clockwise or counter clockwise.
Letters	Memorize a set of letters and update by mentally shifting them up to three positions forward or backward in the alphabet.
Locations	Memorize the locations of a set of circles in a grid and update by mentally shifting them to an adjacent cell as indicated by an arrow.
Digits	Memorize a set of digits and update by applying simple arithmetic operations to them.
Binding training	
Fractal-location	Memorize a series of associations between fractals and their location in a row of boxes on the grid.
Noun-verb	Memorize a series of associations between nouns and verbs.
Color-location	Memorize a series of associations between colored circles and their locations in a 4 x 4 grid.
Symbol-digit	Memorize a series of associations between mathematical symbols and digits.
Mixed-paradigm training	
Memory updating	Memorize the locations of a set of circles in a 4 x 4 grid and update by mentally shifting them to an adjacent cell.
Binding	Memorize a series of associations between colored triangles and their locations in a 4 x 4 grid.
Complex span	Memorize a series of positions of squares in a 5 x 5 grid interleaved by a distractor task.

Note. Detailed description of the tasks can be found in the original publications (De Simoni & von Bastian, under revision; Guye & von Bastian, 2017).

Binding Training. The Young-Binding sample practiced four binding tasks (adapted from Wilhelm et al., 2013). In these tasks, participants had to remember associations between elements (e.g., noun and verbs or objects and their locations in a grid) presented sequentially for 900 ms (noun-verb and symbol-digit) or 1800 ms (fractal-location and color-location) each. After memorization, each association was probed in random order with one of the elements given as cue. Half of the probes were positive (i.e., exact matches), whereas negative probes could be distractors (i.e., probes not presented in the current trial, 25 % of probes) or intrusions (i.e., probes that were presented in the current trial, but associated with a different element, 25 % of probes). Task difficulty was adjusted to individual performance by increasing the set size (i.e., number of sequentially presented pairs) and reducing the time limit to respond to the probes.

MIXED-PARADIGM TRAINING. Mixed-paradigm training consisted of a memory updating task (adapted from De Simoni & von Bastian, under revision; Schmiedek et al., 2014), a binding task (Oberauer, 2005), and a figural-spatial complex span task (von Bastian & Eschen, 2016).

The memory updating task was identical to the locations task practiced by the Young-Updating sample. Participants first had to memorize the locations of colored circles presented simultaneously in a 4 x 4 grid for 500 ms per item. After the presentation of the circles, an arrow was presented alongside one of the circles centrally on the screen for 500 ms. The circle had to be mentally shifted up, down, left, or right to the adjacent cell as indicated by the arrow. Participants indicated the new position of the circle by mouse click in the blank grid. As in the Young-Updating Sample updating training, trials comprised nine updating steps, with half of the trials using a cue presented for 500 ms to indicate which of the circles had to be updated.

The binding task was similar to the ones practiced by the Young-Binding sample. Participants had to memorize a series of locations of colored triangles in a 4 x 4 grid. Each item was presented for 900 ms followed by a 100 ms inter-stimulus interval. During recognition, each association was probed by presenting a triangle in a location in the grid, and participants had to decide whether it matched the triangle that was previously presented at that position. Across all trials, 50 % of the probes were matches, 25 % were distractors, and 25 % were intrusions.

For the complex span task, participants had to memorize a series of red in a 5 x 5 grid, each presented for 1000 ms. Each trial of the series was interleaved by a distractor task, in which participants had to decide whether the long side of an L-shaped figure within the grid was oriented vertically or horizontally. Response time during the distractor task was limited to 3000 ms. During recall, participants had unlimited time to indicate the grid positions in correct serial order by mouse-click.

In all three tasks, difficulty was adjusted by increasing the set size and reducing the response time limit. For the complex span task, time to respond to the distractor task was limited, and for the binding and memory updating tasks time to respond during the retrieval phase was reduced.

ADAPTIVE TASK DIFFICULTY. All participants started training on the same level of task difficulty. To maximize the time participants were exposed to challenging task demands, we ensured that participants quickly reached their individual baseline cognitive performance limit by implementing a fast-evaluating adaptive algorithm during the first training session. Participants' performance was evaluated after every 10 % of trials in the younger samples, and every 7 % of trials in the older sample (corresponding to one trial in the Young-Updating sample and the Old-Mixed sample, and two trials in the Young-Binding sample). If participants reached a performance criterion (i.e., accuracy above 85 % in the younger samples, 80 % in the older sample), task difficulty was raised by reducing the response time limit (by 500 ms in the younger samples and 300 ms in the older sample) for four subsequent level-ups, or by increasing the set size by one additional memorandum every fifth level-up (which also reset the response time limit to the starting value). After the first session, performance was evaluated after every 40% of trials (corresponding to five trials in the Young-Updating sample, ten trials in the Young-Binding sample and six trials in the Old-Mixed sample). The first training session started with a set size of two and a response time limit of 3500 ms per response for the younger samples, and 5000 ms per response in the older sample. The maximum set size was set to eight in the Young-Updating and the Old-Mixed samples and seven in the Young-Binding sample.

Assessment of Individual Differences Variables

Individual differences variables were assessed prior to training, except for motivation, which was assessed at the end of the respective training sessions (see below). Participants completed most computer-based questionnaires at home. Older adults completed the following questionnaires during an individual in-lab assessment at the University of Zurich: a demographic questionnaire, a computer- and Internet questionnaire, and an adapted German, multiple-choice version of the Everyday Performance Test (EPT; Willis & Marsiske, 1993). Mean rating was used as the dependent variable for the questionnaire measures.

Demographics. Age and gender were assessed with a demographic questionnaire.

Real-world Cognition. Education level was assessed on a scale ranging from 0 to 7 (0 = *no formal education*, 7 = *doctorate*). As younger adults were only included in the study if they obtained at least a higher education entrance qualification (corresponding to education level 4), variance in this measure was limited. Thus, we refrained from using education level as a predictor in younger adults. Older adults additionally completed the Cognitive Failure Questionnaire (CFQ; Broadbent et al., 1982), assessing self-reported failures in perception, memory, and motor function. Items such as “Do you find you forget people’s names?” were rated on a 5-point scale (0 = *never*, 4 = *very often*). Further, we assessed older adults’ everyday problem solving abilities using an adapted multiple-choice version of the EPT (Willis & Marsiske, 1993). The EPT is an objective assessment of everyday competence to perform complex tasks of daily living. Participants were presented with 15 everyday tasks (e.g., a recipe for twelve biscuits) and asked to solve two problems associated with each stimulus (e.g., calculate the amount of flour to bake half of the biscuits) by choosing one of four answers. EPT score represents the number of correctly solved items within 45 minutes.

MOTIVATION. In the younger samples, participants' training motivation was assessed at the beginning of and mid-way through training (sessions 1 and 10) using an adapted version of the Questionnaire on Current Motivation (QCM; Rheinberg, Vollmeyer, & Bruns, 2001). On a 7-point scale (1 = *disagree*, 7 = *agree*) they had to rate items such as "I am fully determined to give my best during training". In addition, the younger participants completed an adapted version of the Intrinsic Motivation Inventory (IMI; Deci & Ryan, 2016) at the end of the last training session, rating items such as "Today's training session was fun to do" on a 7-point scale (1 = *does not apply at all*, 7 = *does apply very well*). In the older sample, participants' training motivation was assessed at the beginning of and mid-way through training (sessions 2 and 14) using an adapted version the IMI (Deci & Ryan, 2016). Because the motivation measures were highly correlated in the younger (rs $\geq .48$, ps $< .001$) and older samples ($r = .76$, $p < .001$) across time points, we computed one single motivation composite score by averaging the z-transformed scores.

COGNITION RELATED BELIEFS. Beliefs were measured using four different constructs. First, we assessed participants' passion and perseverance for long-term goals using the 12-item Grit scale (Duckworth et al., 2007). Items such as "I finish whatever I begin" were rated on a 5-point scale (1 = *not like me at all*, 5 = *very much like me*). Second, we assessed the degree to which participants enjoy effortful cognitive activities using the 16-item[1] NFC scale (Cacioppo & Petty, 1982). Items (e.g., "I really enjoy a task that involves coming up with new solutions to problems") were rated on a 7-point scale (1 = *strongly disagree*, 7 = *strongly agree*). Third, participants' implicit beliefs about the malleability of intelligence was assessed using the TIS (Dweck, 2000). Items such as "No matter who you are, you can significantly change your intelligence level" were rated on a 6-point scale (1 = *strongly disagree*, 6 = *strongly agree*). Higher levels indicate an incremental view (a "growth mindset", i.e., viewing intelligence as a malleable, changeable construct). Finally, to assess participants' sense of perceived self-efficacy, we administered the General Self-Efficacy scale (GSE; Schwarzer & Jerusalem, 1995). Participants rated the items (e.g., "I can always manage to solve difficult problems if I try hard enough") on a 4-point scale (1 = *not at all true*, 4 = *exactly true*). Younger adults

[1] In the older sample, the 33-item version was administered. To match the younger samples, we only included the 16 items from the short version in the present analyses.

additionally completed an adapted version of the Self-Efficacy to Regulate Exercise scale (EXSE; Bandura, 2006). Participants rated the items (e.g., "How certain are you that you can get yourself to perform your training routine regularly when you have other time commitments") on a visual analogue scale ranging from 1 to 100.[2]

PERSONALITY. Personality traits were assessed using the 60-item NEO Five Factor Inventory (NEO-FFI; Costa & McCrae, 1992), including subscales for neuroticism, agreeableness, openness, conscientiousness, and extraversion. All items were rated on a 5-point scale (0 = *strongly disagree*, 4 = *strongly agree*).

LEISURE ACTIVITIES. Leisure activities were assessed using an adapted version of the Adult Leisure Activity Questionnaire (Jopp & Hertzog, 2010). Across 11 categories (i.e., physical, developmental, and experiential activities, activities with close social partners, group-centered public activity, religious activities, crafts, game playing, TV watching, travel, and technology use), participants indicated how often they partook in these activities on a 6-point scale (1 = *never*, 6 = *daily*).

COMPUTER LITERACY AND TRAINING EXPERIENCE. Older participants completed a questionnaire regarding their computer and Internet experience. Participants were asked "How confident do you feel using the computer?" and responded on a 7-point scale (1 = *not confident at all*, 7 = *very confident*). Further, participants were asked whether they had any previous cognitive training experience (i.e., through commercially available training programs and / or through participating in other studies).

6.3.3. DATA ANALYSIS

We fitted LGC models to the training data (1) to estimate the individual trajectories of performance change over time and (2) to investigate the effect of baseline cognitive performance on change in training performance, and (3) to identify possible individual differences that predict change in training performance. Ideally, all training sessions would have been included individually in the models (see also Bürki et al., 2014). However, due to the relatively small sample sizes and to increase the signal-to-noise ratio, we reduced the data to five training blocks for each sample by averaging across four sessions in the younger adults (i.e., sessions 1-4, 5-9, 10-14, 15-20) and five sessions in the older adults (i.e., sessions 1-5, 6-

[2] As the two measures for self-efficacy were not correlated ($r = 0.03$, $p = .715$), we analyzed both measures separately rather than computing a composite score.

10, 11-15, 16-20, 21-25). Further, as we were interested in estimating and predicting general rather than task-specific WM training performance, we used an average of the set size achieved at the end of each session across the four binding or memory updating tasks in the younger adults, and across the three training tasks in the older adults as dependent measure.

By modeling two latent variables, the intercept and the slope, LGC modeling allows for parsimoniously describing both linear and non-linear longitudinal trajectories within the SEM framework by accounting for error variance in the manifest variables. Whereas the value in the dependent variable at the beginning of training (μ_i = baseline cognitive performance) is represented by the intercept, the rate of change in the dependent variable (μ_s = increase / decrease in cognitive training performance) is expressed by the slope. Both latent factors are defined by a set of manifest variables (i.e., the training blocks). The model further allows for individual variation in the intercept (σ^2_i = variance in baseline cognitive performance) and the slope (σ^2_s = variance in change of training performance), and this variance can in turn be predicted by additional variables (i.e., individual differences). The covariance between the intercept and the slope ($\sigma_{i,s}$) indicates the degree to which baseline performance and change of training performance are correlated, with a positive covariation supporting a magnification effect, and a negative covariation supporting a compensation effect. Finally, the model includes error covariances ($\sigma_{\varepsilon,\varepsilon}$) accounting for correlated error terms ($\varepsilon_{1\text{-}5}$) between the adjacent training blocks. Error variances ($\sigma^2\varepsilon_{1\text{-}5}$) were constrained to be equal across the five error terms.

Model fit was evaluated using the chi-square statistic (χ^2), the standardized root-mean-square residual (SRMR), and the comparative fit index (CFI). Conventionally, fit is indicated by values between 0 and 2*df* for the χ^2, by values smaller than 0.08 for the SRMR and greater than 0.95 for the CFI (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003). Although the root-mean-square error of approximation (RMSEA) is a popular measure of goodness-of-fit, we do not report it following the recent suggestion of Kenny, Kaniskan, and McCoach (2015). Using Monte Carlo simulations, they showed that the RMSEA tends to over-reject properly specified models with small degrees of freedom, which is the case for all our baseline models (*df*s = 7).

All analyses were conducted in R (version 3.2.3; R Core Team, 2015) using the “lavaan” package (version 0.5.23; Rosseel, 2012). Figures depicting training performance were conducted using the “longCatEDA” package (version 0.31; Tueller, Van Dorn, & Bobashev, 2016). The package depicts categorical longitudinal data (in our case the dependent variable set size) by using shades of color instead of vertical position to indicate changes on categorical variables over time.

6.4. RESULTS

Data and analyses scripts are available on the Open Science Framework (https://osf.io/qgkp2/). First, to test whether participants training performance increased over the course of the intervention and whether this increase follows a linear or non-linear pattern, we ran three baseline models for each sample (i.e., a no-growth, a linear growth, and a non-linear growth model). We selected the best fitting model using nested model comparisons. Second, we investigated whether baseline cognitive performance is associated with change in training performance and, if so, in which direction. Third, to examine how individual differences are associated with change in training performance, we included the individual differences variables to predict cognitive training trajectories.

To avoid potential issues caused by multicollinearity of predictors, we ran separate models for (1) demographic variables, (2) real-world cognition, (3) motivation, (4) cognition-related beliefs, (5) personality, (6) leisure activities, and (7) computer literacy and training experience. To estimate multicollinearity within the predictor categories, we assessed the Variance Inflation Factor (VIF) in both younger and older samples. The VIFs indicated no signs of multicollinearity, with the highest VIF = 2.18 (see also correlation coefficients in Tables C1 and C2 in the Appendix C). For each of these seven models, all measures were included simultaneously and regressed on the latent intercept and slope concurrently, although the primary interest lies on the prediction of change in training performance (i.e., the slope). Ordinal and metric predictors were *z*-transformed prior to data analysis.

6.4.1. MISSING DATA

Data were included for analyses for all participants who performed above chance level during at least 75 % of training sessions (i.e., ≥ 15 sessions for the younger samples, and ≥ 19 sessions for the older sample). We did not include data from three older participants because they (contrary to the instructions) concurrently trained on two computers on two different levels of difficulty. One older participant had to re-install the training software after six training sessions due to technical issues and we used the following 19 sessions for data analyses.

All participants from the Young-Updating sample completed 20 training sessions. However, due to a programming error, the feedback presented during training was incorrect for two participants for the first 2 and 4 sessions, respectively. Consequently, we treated the data from those sessions as missing. In the Young-Binding sample, most participants completed 20 sessions (*M* = 19.83, *SD* = 0.70, range = 15-20). However, four participants did not complete one training session, one participant did not complete two training sessions, and one participant restarted training after 15 sessions. Therefore, we also treated those sessions as missing. Also, most older participants completed 25 sessions (*M* = 24.85, *SD* = 0.98, range = 19-28), except for three participants who completed less due to scheduling problems (i.e., 21, 23, and 24 sessions) and the one person who re-installed the training software (i.e., 19 sessions). If participants completed more than 25 training sessions, these additional sessions were omitted from data analysis.

As we only had missing data for continuous variables but not for categorical or ordinal variables (e.g., gender or education), missing data were handled using Full Information Maximum Likelihood (FIML) estimation, thereby using all available information for estimating the model (see also Grimm, Ram, & Estabrook, 2017).

6.4.2. Bayes Factors

We computed BFs for the effect of each predictor on the slope or intercept, allowing for quantifying the evidence for both the alternative hypothesis (i.e., predictor is associated with slope or intercept) and the null hypothesis (i.e., predictor is not associated with slope or intercept). Further, we computed BFs for the variances of the intercept and the slope, as well as for the covariance between the intercept and the slope. BFs were approximated based on the Bayesian Information Criterion (BIC), which evaluates model fit based on the log-likelihood taking the degrees of freedom into account, with a lower BIC reflecting a better model fit. The BF is computed using the difference in BICs when comparing the model freely estimating the predictor of interest and the model in which the predictor of interest is fixed to zero (Wagenmakers, 2007):

$BF_{H1} = \exp(0.5*(BIC_2 - BIC_1)$,

with BIC_1 being the BIC for the alternative model freely estimating the predictor of interest, and BIC_2 being the BIC for the identical model with the predictor of interest fixed to zero (i.e., the null model). BFs range from 0 to infinity, with higher values indicating stronger evidence for the alternative model. BFs are evaluated according to an adapted version of Wetzels and Wagenmakers (2012) to facilitate verbal interpretation (see Table 11). For example, a BF of 3 indicates that the data is three times more likely to occur under the alternative hypothesis. BFs favoring the null model (i.e., BFs < 1) are expressed as 1/BF.

Table 11

Verbal Labels to Guide Interpretation of Bayes Factors

BF	Interpretation
> 100	Decisive
30-100	Very strong
10-30	Strong
3-10	Substantial
1-3	Ambiguous
1	No evidence

Note. Adapted from Wetzels and Wagenmakers (2012).

6.4.3. Specification of the Baseline Model

To identify the best fitting baseline model, we conducted several nested model comparisons for each sample and assessed whether there was a significant improvement of the relative fit (see Table 12). We compared three models: a no growth curve model assuming no change in cognitive performance (Model 1), a linear model assuming a linear change in cognitive performance (Model 2), and a non-linear model assuming a non-linear change in cognitive performance (Model 3). Model 3 was modeled according to Kline (2016) by fixing the first two coefficients of the slope factor to constants (0, 1) and freeing the remaining coefficients for the slope factor. This specification allows for estimating an empirical curvilinear trend that optimally fits the data. For all samples, Model 3 fitted the data significantly better than Models 1 and 2.

Table 12

Nested Model Comparisons and Fit Indices for Baseline Latent Growth Curve Models

	χ^2	df	SRMR	CFI	Model comparison	$\Delta\chi^2$	Δdf
Young-Updating							
Model 1	**435.47**	13	1.15	.22	-	-	-
Model 2	**52.56**	10	0.08	.92	1 vs. 2	**382.91**	3
Model 3	4.04	7	0.02	1.00	2 vs. 3	**48.52**	3
Young-Binding							
Model 1	**534.73**	13	1.79	.12	-	-	-
Model 2	**142.11**	10	0.16	.78	1 vs. 2	**392.62**	3
Model 3	**23.22**	7	0.04	.97	2 vs. 3	**118.89**	3
Old-Mixed							
Model 1	**413.89**	13	0.82	.23	-	-	-
Model 2	**32.88**	10	0.08	.96	1 vs. 2	**381.01**	3
Model 3	11.83	7	0.05	.99	2 vs. 3	**21.06**	3

Note. Bold values represent significant χ^2 statistics ($p < .05$)

6.4.4. Latent Analysis of Training Performance

Results for the baseline models are summarized in Figure 9. Training performance for each training task is visualized in Figure 10 for younger adults, and Figure 11 for older adults. Training performance across tasks for the three samples is visualized in Figure 12.

The non-linear baseline LGC model fitted the data from the Young-Updating sample well, $\chi^2(7) = 4.04$, $p = .775$, SRMR = 0.02, CFI = 1.00. Results indicate that individuals started training at block 1 with a mean set size of 2.98 ($\mu_i = 2.98$, $SE = 0.05$, $p < .001$) and significantly increased their performance by 0.49 ($\mu_s = 0.49$, $SE = 0.03$, $p < .001$), resulting in estimated mean levels of training performance across the five blocks of 2.98 (block 1), 3.47 (block 2), 3.86 (block 3), 4.19 (block 4), and 4.45 (block 5).[3] We found strong evidence for a positive association between the intercept and the slope ($\sigma_{i,s} = 0.03$, $SE = 0.01$, $p = .004$, $BF_{H1} = 11.98$), suggesting that individuals who showed higher baseline cognitive performance also showed larger training performance gains. Further, there was decisive evidence for individual differences in the variance of baseline cognitive performance ($\sigma^2_i = 0.15$, $SE = 0.03$, $p < .001$, $BF_{H1} > 100$) and change therein ($\sigma^2_s = 0.03$, $SE = 0.01$, $p < .001$, $BF_{H1} > 100$).

In the Young-Binding sample, the non-linear baseline LGC model's fit was acceptable,

[3] Estimated means are determined by the factor mean of the intercept μ_i and pattern coefficients λ and were computed by the formula: estimated mean = $\mu_i + \lambda * \mu_s$ (see Kline, 2016 for details).

$\chi^2(7) = 23.22$, $p = .002$, SRMR = 0.04, CFI = 0.97. The Young-Binding sample started training at block 1 with a mean set size of 3.46 ($\mu_i = 3.46$, $SE = 0.05$, $p < .001$) and significantly increased their performance by 0.69 ($\mu_s = 0.69$, $SE = 0.04$, $p < .001$), resulting in estimated mean levels of training performance across the five blocks of 3.46 (block 1), 4.15 (block 2), 4.62 (block 3), 4.94 (block 4), and 5.19 (block 5). Again, we found decisive evidence for a positive association between the intercept and the slope ($\sigma_{i,s} = 0.05$, $SE = 0.01$, $p < .001$, $BF_{H1} > 100$), suggesting that individuals who showed higher baseline cognitive performance also showed larger training performance gains. Further, we found decisive evidence for individual differences in the variance of baseline cognitive performance ($\sigma^2_i = 0.12$, $SE = 0.03$, $p < .001$, $BF_{H1} > 100$) and change therein ($\sigma^2_s = 0.05$, $SE = 0.01$, $p < .001$, $BF_{H1} > 100$).

Finally, the non-linear baseline LGC model fit the data from the Old-Mixed sample well, $\chi^2(7) = 11.83$, $p = .106$, SRMR = 0.05, CFI = 0.99, and showed that older adults started training at block 1 with a mean set size of 3.08 ($\mu_i = 3.08$, $SE = 0.05$, $p < .001$) and significantly increased their performance by 0.40 ($\mu_s = 0.40$, $SE = 0.03$, $p < .001$), resulting in estimated mean levels of training performance across the five blocks of 3.08 (block 1), 3.48 (block 2), 3.84 (block 3), 4.13 (block 4), and 4.38 (block 5). We found ambiguous evidence for the absence of an association between the intercept and the slope ($\sigma_{i,s} = 0.02$, $SE = 0.01$, $p = .056$, $BF_{H0} = 1.39$), but again we found decisive evidence for individual differences in the variance of baseline cognitive performance ($\sigma^2_i = 0.17$, $SE = 0.03$, $p < .001$, $BF_{H1} > 100$) and change therein ($\sigma^2_s = 0.02$, $SE = 0.00$, $p < .001$, $BF_{H1} > 100$).

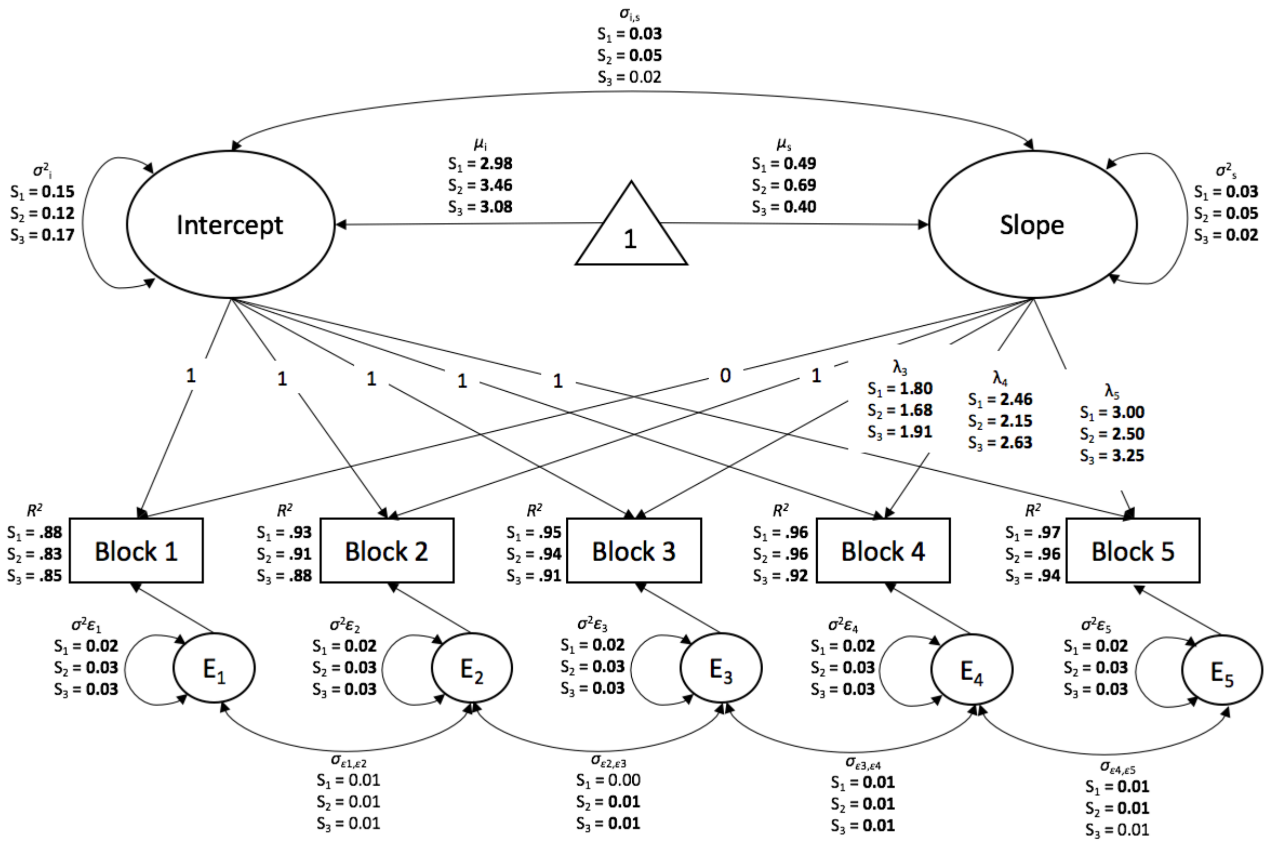

Figure 9. Baseline non-linear latent growth curve model of change in training performance. Bold numbers indicate significance ($p < .05$). Unstandardized estimates are presented for the Young-Updating sample (S_1), the Young-Binding sample (S_2), and the Old-Mixed sample (S_3). Squares represent observed variables (training blocks 1-5), circles represent latent factors, and the triangle is modeled to represent the means of the latent factors (μ_i = mean of the intercept, μ_s = mean of the slope). σ^2_i = variance of the intercept; σ^2_s = variance of the slope; $\sigma_{i,s}$ = covariance of intercept and slope; $\lambda_{3\text{-}5}$ = pattern coefficients; $E_{1\text{-}5}$ = error terms; $\sigma^2\varepsilon_{1\text{-}5}$ = error variances; $\sigma_{\varepsilon,\varepsilon}$ = error covariances.

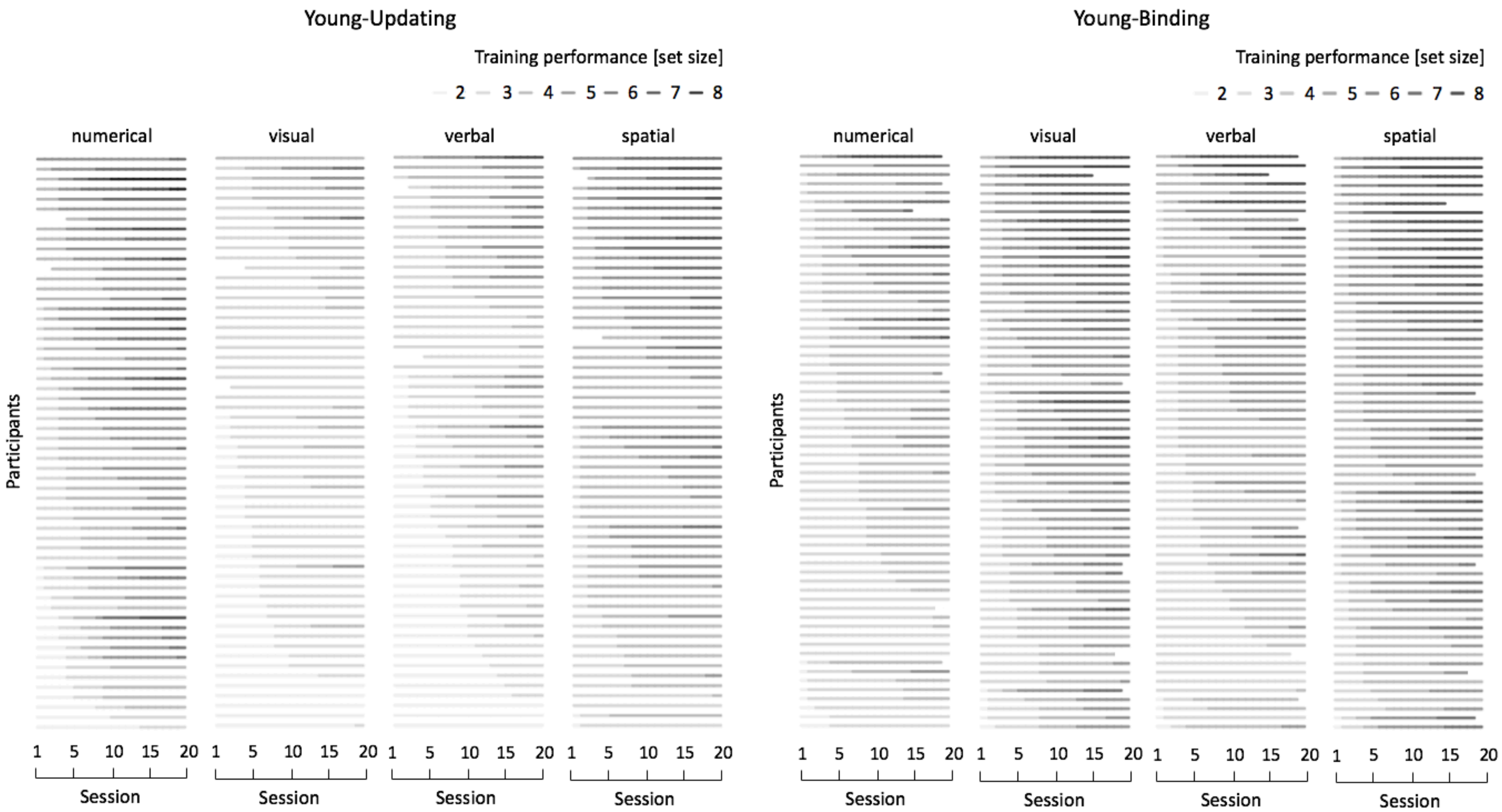

Figure 10. Growth curve plot of task-specific training performance for the Young-Updating and Young-Binding samples. Each line represents an individual, ordered vertically separately for each task using the sorter function implemented in the "longCatEDA" package (Tueller et al., 2016). Shades of grey represent set size achieved at the end of each training session. Thus, lines are darker with increasing training performance and task difficulty.

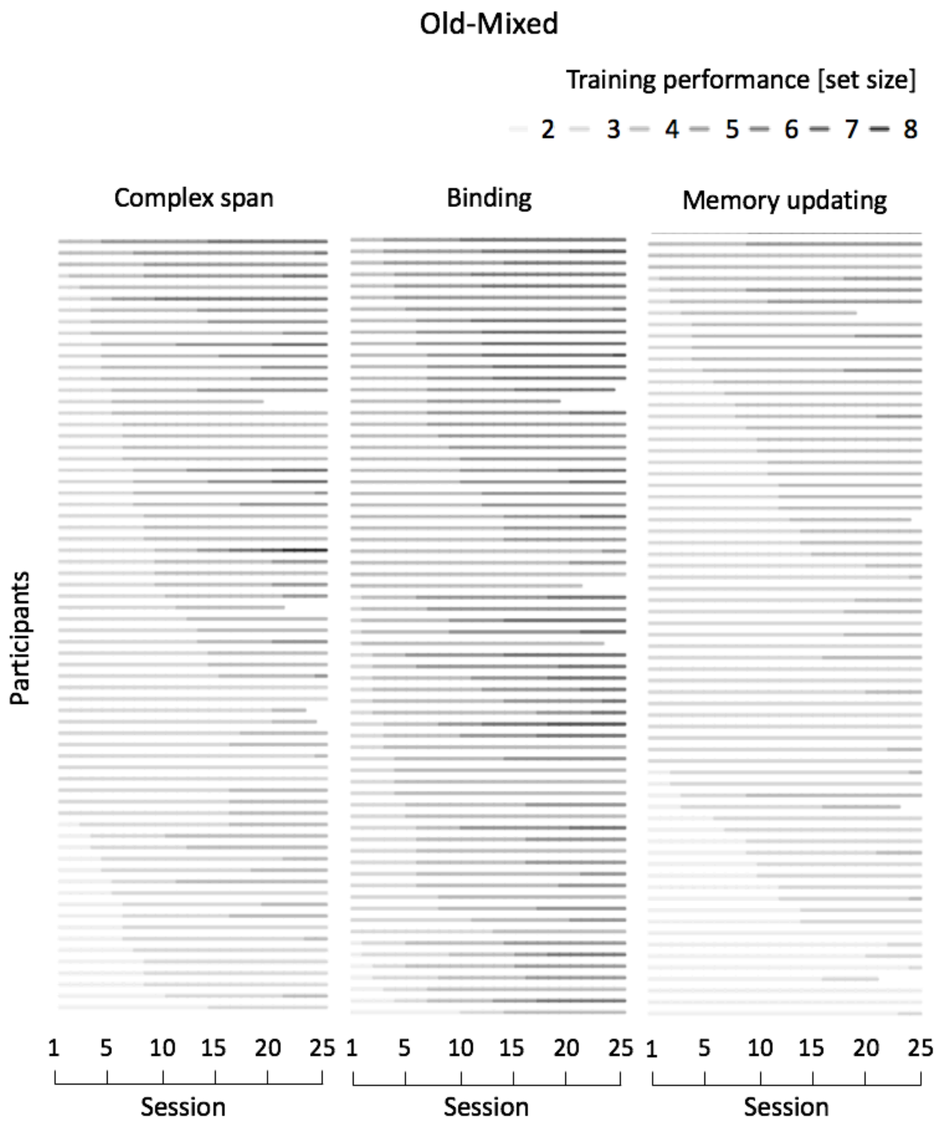

Figure 11. Growth curve plot of task-specific training performance for the Old-Mixed Sample. Each line represents an individual, ordered vertically separately for each task using the sorter function implemented in the "longCatEDA" package (Tueller et al., 2016). Shades of grey represent set size achieved at the end of each training session. Thus, lines are darker with increasing training performance and task difficulty.

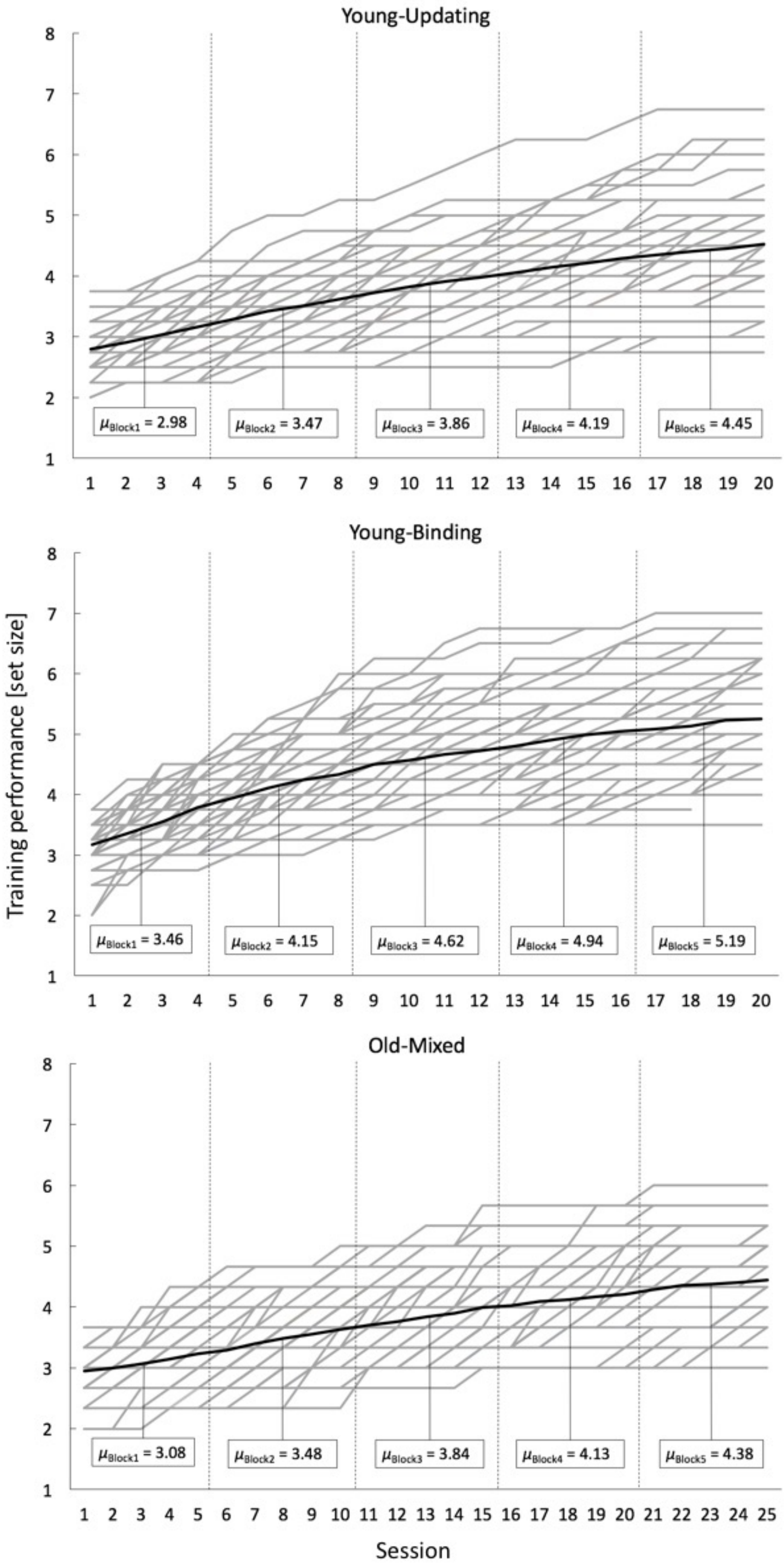

Figure 12. Training performance averaged across training tasks for each individual (grey) and on the group level (black). Estimated means are presented for each training block.

6.4.5. Association of Individual Differences with Change in Training Performance and Baseline Cognitive Performance

Descriptive statistics for the individual differences variables are presented in Table 13. To predict training trajectories, we included all variables measuring the same aspect of individual differences simultaneously in the baseline model. Note that although results will be reported separately for the slope and the intercept, the individual differences variables were regressed on both latent factors concurrently.

Individual Differences Predicting Change in Training Performance

Overall, we found only limited evidence for individual differences predicting change in training performance, with most estimates supporting the null hypothesis (see Table 14). There was only one exception. In the Old-Mixed sample, we found substantial evidence for a negative association of growth mindset with change in training performance (b = -0.37, p = .005, BF_{H1} = 3.26), however indicating that individuals who believed more strongly that intelligence is malleable showed less increase in training performance.

For most other individual differences, including demographic variables, real-world cognition, motivation, personality, leisure activities, and computer literacy and training experience, we found evidence against an association with change in training performance, with at least substantial evidence in favor for the null hypothesis ($BF_{H0} \geq 3$).

Table 13

Descriptive Statistics for Individual Differences Variables

Individual differences	Sample		
	Young-Updating	Young-Binding	Old-Mixed
Demographics			
Age	22.57 (2.99)	24.77 (4.03)	70.40 (3.72)
Gender (f/m)	39/19	45/19	30/38
Real-world cognition			
Education	5 (0.00)	5 (0.00)	5 (1.48)
CFQ	-	-	1.20 (0.42)
EPT	-	-	25.54 (3.05)
Motivation	-0.08 (0.95)	0.09 (0.79)	5.15 (0.60)
Cognition-related beliefs			
Grit	2.76 (0.60)	2.74 (0.61)	3.74 (0.52)
TIS	4.47 (0.89)	4.31 (1.01)	3.98 (1.06)
GSE	2.98 (0.37)	3.00 (0.35)	3.06 (0.37)
EXSE	65.66 (18.22)	62.84 (17.38)	-
NFC	5.07 (0.69)	5.03 (0.68)	5.24 (0.84)
Personality			
Neuroticism	1.70 (0.63)	1.60 (0.65)	1.13 (0.53)
Agreeableness	2.73 (0.60)	2.81 (0.42)	2.82 (0.34)
Extraversion	2.40 (0.65)	2.39 (0.61)	2.39 (0.50)
Openness	2.73 (0.57)	2.77 (0.54)	2.73 (0.43)
Conscientiousness	2.71 (0.58)	2.75 (0.53)	2.90 (0.51)
Leisure activities			
Crafts	-	-	2.31 (1.17)
Developmental activities	-	-	2.41 (0.46)
Experiential activities	-	-	3.40 (0.68)
Game playing	-	-	2.56 (0.89)
Physical activities	-	-	3.13 (0.90)
Religious activities	-	-	2.43 (1.45)
Activities with close social partner	-	-	3.15 (0.55)
Group centered public activities	-	-	1.77 (0.55)
Technology use	-	-	3.14 (0.79)
TV watching	-	-	3.62 (0.90)
Travel	-	-	2.53 (0.57)
Training / Computer			
Computer literacy	-	-	5.04 (1.52)
Training experience (y/n)	-	-	23/45

Note. Values are means and standard deviations in parentheses (median and median absolute deviation in parentheses for education). CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test; TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

INDIVIDUAL DIFFERENCES PREDICTING BASELINE COGNITIVE PERFORMANCE

We found some evidence for individual differences predicting baseline cognitive performance, with all evidence, however, being observed in the older adults only (see Table 15). We found decisive evidence for an association of gender with baseline cognitive performance (b = 0.45, p < .001, BF_{H1} > 100), indicating that male individuals started training at a higher level of performance. Further, there was substantial evidence that age was negatively associated with baseline cognitive performance (b = -0.32, p = .002, BF_{H1} = 5.69), indicating that within the older age group, younger individuals showed higher baseline cognitive performance. Regarding real-world cognition, we found strong evidence for a positive association of EPT performance with baseline cognitive performance (b = 0.39, p < .001, BF_{H1} = 18.34), indicating that individuals who performed better in the EPT also showed higher baseline cognitive performance. In addition, we found substantial evidence for a positive association of grit with baseline cognitive performance (b = 0.37, p = .002, BF_{H1} = 6.54), indicating that grittier individuals showed higher baseline cognitive performance. Regarding personality, we found very strong evidence for a negative association of extraversion with baseline cognitive performance (b = -0.44, p < .001, BF_{H1} = 43.40), indicating that individuals scoring high on extraversion showed lower baseline cognitive performance. Finally, we found substantial evidence for a negative association of religious activities with baseline cognitive performance (b = -0.34, p = .003, BF_{H1} = 5.01), indicating that individuals with high levels of religious activities (e.g., frequent church attendance) started training at a lower level of performance. For most other individual differences, however, we found evidence against an association with baseline cognitive performance, with at least substantial evidence in favor for the null hypothesis ($BF_{H0} \geq 3$).

Table 14

Associations of Individual Differences with Change in Cognitive Performance

	Young-Updating				Young-Binding				Old-Mixed			
Individual differences	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}
Demographic variables												
Age	-0.30	.014	1.61	0.62	-0.26	.046	0.74	1.35	0.12	.396	0.17	**5.80**
Gender	0.15	.244	0.25	**3.98**	0.27	.035	0.88	1.14	0.01	.937	0.12	**8.22**
Real-world cognition												
Education	-	-	-	-	-	-	-	-	0.31	.021	1.24	0.81
CFQ	-	-	-	-	-	-	-	-	0.07	.600	0.14	**7.19**
EPT	-	-	-	-	-	-	-	-	0.09	.511	0.15	**6.66**
Motivation	0.08	.563	0.15	**6.46**	0.24	.058	0.63	1.59	-0.13	.366	0.18	**5.54**
Cognition-related beliefs												
Grit	0.19	.138	0.37	2.71	0.11	.439	0.17	**5.97**	-0.02	.864	0.12	**8.13**
TIS	-0.29	.028	1.06	0.95	-0.16	.250	0.24	**4.23**	-0.37	.005	**3.26**	0.31
GSE	-0.12	.467	0.17	**5.87**	-0.20	.121	0.38	2.60	-0.07	.673	0.13	**7.55**
EXSE	-0.11	.424	0.18	**5.57**	0.24	.070	0.56	1.79	-	-	-	-
NFC	0.07	.698	0.14	**7.07**	0.09	.562	0.15	**6.77**	0.05	.767	0.13	**7.89**
Personality												
Neuroticism	0.01	.961	0.13	**7.61**	0.00	.978	0.12	**8.00**	-0.13	.412	0.17	**5.93**
Agreeableness	-0.09	.532	0.16	**6.28**	0.05	.683	0.14	**7.37**	0.12	.441	0.16	**6.15**
Extraversion	-0.20	.196	0.29	**3.44**	-0.29	.037	0.85	1.18	0.08	.614	0.14	**7.27**
Openness	-0.05	.688	0.14	**7.03**	0.04	.784	0.13	**7.71**	-0.32	.018	1.34	0.75
Conscientiousness	-0.27	.038	0.88	1.14	-0.08	.562	0.15	**6.77**	-0.29	.055	0.65	1.54
Leisure activities												
Crafts	-	-	-	-	-	-	-	-	-0.07	.637	0.14	**7.38**
Developmental activities	-	-	-	-	-	-	-	-	0.16	.337	0.19	**5.27**
Experiential activities	-	-	-	-	-	-	-	-	-0.09	.652	0.13	**7.46**
Game playing	-	-	-	-	-	-	-	-	0.05	.696	0.13	**7.64**
Physical activities	-	-	-	-	-	-	-	-	-0.06	.646	0.13	**7.42**
Religious activities	-	-	-	-	-	-	-	-	-0.05	.703	0.13	**7.67**

Activities with social partner	-	-	-	-	-	-	-	-	0.00	.992	0.12	**8.24**
Public activities	-	-	-	-	-	-	-	-	0.14	.380	0.18	**5.66**
Technology use	-	-	-	-	-	-	-	-	-0.19	.193	0.27	**3.68**
TV watching	-	-	-	-	-	-	-	-	-0.13	.352	0.19	**5.40**
Travel	-	-	-	-	-	-	-	-	-0.34	.011	1.84	0.54
Computer/Training												
Computer literacy	-	-	-	-	-	-	-	-	-0.28	.039	0.80	1.25
Training experience	-	-	-	-	-	-	-	-	0.05	.702	0.13	**7.66**

Note. Bold values represent BF ≥ 3 indicating substantial evidence for the respective model. BF_{H1} represent BF favoring the alternative model, BF_{H0} represent BF favoring the null model. *b* = standardized estimates. CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test; TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

Table 15

Associations of Individual Differences with Baseline Cognitive Performance

	Young-Updating				Young-Binding				Old-Mixed			
Individual differences	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}
Demographic variables												
Age	-0.13	.336	0.21	**4.86**	-0.27	.039	0.82	1.22	-0.32	.002	**5.69**	0.18
Gender	0.03	.815	0.13	**7.41**	0.17	.225	0.25	**3.96**	0.45	<.001	**> 100**	0.01
Real-world cognition												
Education	-	-	-	-	-	-	-	-	0.25	.030	1.00	1.00
CFQ	-	-	-	-	-	-	-	-	-0.09	.429	0.17	**6.06**
EPT	-	-	-	-	-	-	-	-	0.39	<.001	**18.34**	0.05
Motivation	0.18	.179	0.31	**3.25**	0.20	.127	0.37	2.71	-0.13	.325	0.19	**5.15**
Cognition-related beliefs												
Grit	0.03	.791	0.14	**7.35**	0.20	.129	0.37	2.71	0.37	.002	**6.54**	0.15
TIS	-0.34	.007	2.72	0.37	0.16	.263	0.23	**4.37**	-0.06	.635	0.14	**7.37**
GSE	0.00	.997	0.13	**7.61**	-0.09	.498	0.16	**6.38**	-0.29	.033	0.95	1.06
EXSE	0.14	.288	0.23	**4.41**	0.23	.080	0.51	1.97	-	-	-	-
NFC	0.23	.149	0.35	2.86	0.15	.310	0.21	**4.86**	0.12	.420	0.17	**5.99**
Personality												
Neuroticism	-0.03	.823	0.13	**7.43**	0.06	.657	0.14	**7.26**	-0.28	.021	1.31	0.76
Agreeableness	-0.16	.274	0.23	**4.28**	0.23	.072	0.55	1.83	0.20	.090	0.47	2.15
Extraversion	0.11	.504	0.16	**6.11**	-0.18	.213	0.26	**3.81**	-0.44	<.001	**43.40**	0.02
Openness	-0.02	.868	0.13	**7.51**	0.15	.247	0.24	**4.21**	-0.04	.722	0.13	**7.74**
Conscientiousness	-0.15	.292	0.22	**4.46**	-0.03	.833	0.13	**7.83**	0.32	.007	2.94	0.34
Leisure Activities												
Crafts	-	-	-	-	-	-	-	-	0.25	.046	0.75	1.33
Developmental activities	-	-	-	-	-	-	-	-	0.24	.085	0.49	2.05
Experiential activities	-	-	-	-	-	-	-	-	-0.31	.061	0.62	1.62
Game playing	-	-	-	-	-	-	-	-	0.08	.514	0.15	**6.68**

Physical activities	-	-	-	-	-	-	-	-	-0.03	.838	0.12	**8.07**
Religious activities	-	-	-	-	-	-	-	-	-0.34	.003	**5.01**	0.20
Activities with social partner	-	-	-	-	-	-	-	-	-0.09	.490	0.15	**6.51**
Public activities	-	-	-	-	-	-	-	-	0.21	.134	0.35	2.83
Technology use	-	-	-	-	-	-	-	-	0.08	.563	0.14	**6.98**
TV watching	-	-	-	-	-	-	-	-	0.07	.572	0.14	**7.03**
Travel	-	-	-	-	-	-	-	-	0.03	.838	0.12	**8.07**
Computer/Training												
Computer literacy	-	-	-	-	-	-	-	-	0.20	.114	0.39	2.57
Training experience	-	-	-	-	-	-	-	-	0.17	.173	0.29	**3.41**

Note. Bold values represent BF ≥ 3 indicating substantial to decisive evidence for the respective model. BF_{H1} represent BF favoring the alternative model, BF_{H0} represent BF favoring the null model. *b* = standardized estimates. CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test; TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

6.4.6. Additional Analyses of the First Training Block

A limitation of our modeling approach is that the intercept represents the mean performance across the first block (i.e., the average set size of the first 4 or 5 training sessions, depending on the sample). Thus, this analysis does not allow to directly predict change in training performance during this first training block in the context of overall change in training performance. Therefore, to investigate how individual differences are associated with baseline cognitive performance at the first training session and change in training performance across the first training block, we additionally ran the same models for the first training block only, with the first training session as the intercept and change modeled across the first four to five training sessions, depending on the sample. Detailed results of these analyses are reported in the Appendix C (see Tables C3 to C6, Figure C13).

Overall, although the BFs were somewhat lower in these additional analyses (possibly due to the increased noise in the non-averaged data), the pattern of results was largely similar to the findings of our primary analyses, with a few exceptions. Whereas a model assuming a non-linear change in training performance still fitted the data of the Old-Mixed sample best, nested model comparisons indicated the best fit for a model assuming a linear change in both younger samples (see Table C3 in the Appendix C). Hence, younger, but not older, adults showed stronger performance increases during the first few sessions than across all sessions. As for the primary analyses, evidence for the variance of baseline cognitive performance and change in cognitive performance was decisive for all samples (see Table C4 in the Appendix C). However, different to the primary analyses, we found substantial evidence for the absence of an association between the intercept and slope in both younger samples. The evidence for this association was again ambiguous for the older adults (see Table C4 in the Appendix C).

Similar to the primary analyses, most predictors were also unrelated to change in training performance over the first few training sessions (see Table C5 in the Appendix C). In addition to the now strong evidence for a negative association with growth mindset (b = -0.44, p = .001, BF_{H1} = 10.37), we found substantial evidence for a negative association with age (b = -0.36, p = .004, BF_{H1} = 3.38), indicating that, within the older sample, younger individuals changed more during the first training block. Taken together with the above finding that the slope followed a linear function in the younger samples, but a non-linear function in the older sample, this suggests that age differences play a bigger role at the beginning of training than at later stages.

Results were also largely similar for the predictors of baseline cognitive performance at the first session, with a few exceptions (see Table C6 in the Appendix C). First, in the Old-Mixed sample, there was substantial evidence for a negative association of general self-efficacy with performance in the first session (b = -0.39, p = .001, BF_{H1} = 7.03). Second, in the Young-Updating sample, we found substantial evidence for a negative association of a growth mindset (b = -0.38, p = .002, BF_{H1} = 5.35). Third, the associations of the intercept with age and religious activities were no longer substantial when analyzing only the first session.

6.5. Discussion

The objectives of the present work were threefold. First, we estimated individual training trajectories. Second, we related baseline cognitive performance (i.e., the intercept) to change in training performance across the training phase (i.e., the slope). Third, we examined the extent to which individual differences were predictive of change in training performance. We modeled LGCs for three WM training interventions in younger and older adults that comprised a broad set of potential individual differences variables previously discussed in the literature, including demographic variables, motivation, cognition-related beliefs, and personality traits. Using Bayesian inference enabled us to evaluate the strength of evidence for the presence as well as the absence of a possible association between individual differences in the above variables and change in training performance.

Performance improved non-linearly across the training phase in all three samples. In line with the magnification account, this change in training performance was positively associated with baseline cognitive performance, indicating that individuals who started off on higher performance levels also improved more throughout the training phase. However, whereas evidence for the presence of this relationship was strong to decisive in the two younger samples, we found ambiguous evidence for the absence of it in the older sample. Finally, although baseline cognitive performance was predicted by individual differences in some variables (i.e., demographics, real-world cognition, cognition-related beliefs, personality, and leisure activities), only 1 out of 29 variables predicted change in training performance, and did so only inconsistently across samples. More specifically, we found that, in the older sample, growth mindset was negatively associated with change in training performance. Taken together, our findings suggest that changes observed during training are best predicted by baseline cognitive performance, with individual differences in demographic variables, real-world cognition, motivation, cognition-related beliefs, personality traits, leisure activities, and computer and training experience playing a negligible role only.

6.5.1. Magnification of Training Performance

In all three samples, individuals substantially increased their performance across the training phase, with a steeper increase at the beginning of the training phase leveling off toward the end of the training phase. Large training effects are an established finding in the literature across various training regimes in both younger (e.g., Brehmer et al., 2012; Jaeggi et al., 2008; Sprenger et al., 2013; von Bastian & Oberauer, 2013), and older adults (e.g., von Bastian, Langer, et al., 2013; Zimmermann et al., 2016; see Karbach & Verhaeghen, 2014 for a meta-analysis), indicating that improving in cognitive tasks is not limited to younger adults, but extends into old age.

The positive association between baseline cognitive performance and change in training performance is in line with studies reporting that general WM performance strongly predicts cognitive learning in associative and category-learning tasks (e.g., Lewandowsky, 2011; Tamez, Myerson, & Hale, 2012) and previous literature on age-related and ability-related magnification effects in the context of cognitive training (e.g., Bürki et al., 2014; Schmiedek et al., 2010). Magnification effects are more typically observed in the context of strategy-based training than process-based training (e.g., Karbach & Verhaeghen, 2014), possibly indicating that the training intervention in this study facilitated strategy acquisition (for a more detailed discussion, see De Simoni & von Bastian, under revision; Guye & von Bastian, 2017). It has been argued that individuals with higher levels of cognitive performance at baseline have more cognitive capacity available to acquire and perform strategies to enhance cognitive efficiency during training (Lövdén et al., 2012).

However, the positive association between baseline cognitive performance and change in cognitive performance was less pronounced in the older sample, providing ambiguous evidence for the absence of this association in the older adults. One possible explanation for this finding is that, although often proclaimed otherwise, older adults in our sample differed somewhat less than younger adults in their training slope (σ^2_s = 0.02 compared to σ^2_s = 0.05 in the Young-Binding and σ^2_s = 0.03 in the Young-Updating samples). Hence, it is possible that power was simply too low to detect the positive relationship, as indicated by the ambiguous BF. Furthermore, future studies are needed to directly compare the association of baseline cognitive ability with change in cognitive performance in younger and older adults in order to draw conclusions regarding age-related differences in magnification effects.

6.5.2. Limited Evidence for Individual Differences Predicting Change in Training Performance

Concerning the debate about the effectiveness of cognitive training interventions, an often-voiced explanation for inconsistencies between the studies is the potential role of individual differences on training outcomes (e.g., Shah et al., 2012), with individually-tailored interventions potentially maximizing the effects of cognitive training. We indeed found substantial variance among individuals in change of training performance in all samples that could be potentially predicted by variables that had been discussed in the past (Katz et al., 2016). Therefore, we examined how (1) demographic variables, (2) real-world cognition, (3) motivation, (4) cognition-related beliefs, (5) personality, (6) leisure activities, and (7) computer literacy and training experience predicted variance in the training trajectories. Based on previous literature, we expected a positive association of motivation, growth mindset, and conscientiousness, and a negative association of age and neuroticism with change in training performance. For all the other individual differences, the analyses were exploratory. However, our results did not support our expectations.

First, we found substantial evidence for the absence of an association of age with change in training performance across the entire training intervention at least in the older sample. However, in our additional analyses we found substantial evidence for a positive association with change in training performance in the first training block for older adults, indicating that age differences might be relevant during early stages of training, but less so later on. In addition, change in training performance was positively associated with baseline performance, implying that age and initial cognitive performance indeed may need to be conceptually separated when examining magnification and compensation effects (von Bastian & Oberauer, 2014).

Second, we found evidence for the absence of an association of change in training performance with previously proposed personality traits such as neuroticism and conscientiousness. Hence, although neuroticism has been reported to be associated with mean training performance and transfer effects (e.g., Studer-Luethi et al., 2012; 2016), it may only play a neligible role in predicting change in training performance. This is in line with previous findings showing no significant association of neuroticism with training gains (Studer-Luethi et al., 2012; 2016).

Fourth and contrary to our expectations, we found evidence for a negative association of growth mindset with change in training performance in the older sample. Similarly, Thompson and colleagues (2013) reported a marginally significant negative association of growth mindset with improvements in a trained WM task in younger adults. We can only speculate about what causes this rather counterintuitive finding, but one possible explanation could be that individuals with high levels of growth mindset are so heavily focused on changing their cognitive performance that they pay too much attention to their cognitive performance, drawing away resources that would be necessary to perform the training tasks efficiently (see also Studer-Luethi et al., 2012).

6.5.3. Limitations

Despite several strengths of the present study, there are some limitations. First, our analyses do not allow for a direct comparison between the three samples. Although they were all undergoing highly similar training regimes, there were slight differences between the interventions regarding the exact tasks being used in the different age-groups (single vs. mixed-paradigm training), and the features of the training interventions (e.g., frequency of the training sessions, monetary reward). Thus, in order to directly compare the presence or absence of the individual differences in younger and older adults, future studies should pursue an age-comparative approach.

Second, the averaging across several training tasks and training sessions to improve the robustness of our performance indicators, was, unavoidably, accompanied some shortcomings. First, averaging across multiple sessions and tasks comes with a loss of more fine-grained information regarding the performance in the single tasks and sessions. Second, it prevented us from predicting early performance changes in context of overall change in training performance (i.e., the first 4 or 5 sessions, but see Appendix C). Using the average across the first few sessions as a measure of baseline cognitive performance comes, however, also with the advantage to reduce noise from two sources of unwanted variance, (1) from training-specific adjustment processes at the beginning of the training (i.e., getting used to the computer, understanding the nature of the training tasks), and (2) from substantial day-to-day variability in cognitive performance (Schmiedek, Lövdén, & Lindenberger, 2013).

Finally, although our group sizes were considerably larger than the median group size in the cognitive training literature ($n = 22$; Lampit et al., 2014), they are still fairly small when using SEM and relying on traditional NHST. In the presence of small sample sizes, p values can vary greatly, known as “the dance of the *p*-values” (Bogg & Laseki, 2015; Cumming, 2011; Halsey et al., 2015; von Bastian et al., in press). To overcome this limitation, we additionally evaluated the evidence for and against the existence of links between the individual differences variables and change in training performance using BFs, as they vary less when power is low (Dienes, 2014). The size of the BFs indicate that our sample sizes were sufficient to provide conclusive evidence for the absence of the majority of investigated associations.

6.6. Conclusion

To the best of our knowledge, our study was the first to comprehensively investigate a broad range of individual differences in cognitive lab and real-world performance, demographics, motivation, cognition-related beliefs, personality traits, leisure activities, as well as computer literacy and training experience, which had previously been discussed to potentially predict change in training performance, in different study populations (i.e., younger and older adults). However, although we found some of the proposed variables predicted baseline cognitive performance, change in training performance was predicted primarily by baseline cognitive performance in the younger adults, suggesting that individuals scoring higher in the beginning of training also showed more pronounced improvements across the training phase.

6.7. APPENDIX C

SUPPLEMENTAL MATERIALS

Table C1

Correlation Coefficients of the Individual Differences for the Young-Updating and Young-Binding

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age		.00	-.04	.15	.03	-.07	-.06	-.04	.16	-.10	-.23	-.02	.03
2. Gender	**.32**		.07	**.28**	.17	-.02	-.02	-.04	.09	-.23	-.21	-.13	-.21
3. Motivation	.16	**.31**		-.05	.12	-.08	**.36**	.16	-.19	.12	.07	-.07	.18
4. Grit	.02	-.07	.04		-.14	-.10	-.05	-.13	.14	**-.33**	**-.30**	-.11	**-.51**
5. TIS	-.07	.04	.12	**-.26**		**.32**	-.03	.25	**-.28**	.11	.21	.12	.07
6. GSE	-.08	.01	.17	-.20	.01		.03	**.56**	**-.67**	.03	**.47**	**.36**	.14
7. EXSE	.03	.17	**.28**	-.20	.07	.04		**.31**	-.17	.18	.23	.24	.13
8. NFC	.15	.16	**.36**	-.09	**.40**	.23	**.27**		**-.45**	-.14	**.42**	**.51**	**.31**
9. Neuroticism	-.16	-.17	-.20	.22	-.19	**-.47**	.01	-.12		-.02	**-.45**	-.13	-.16
10. Agreeableness	-.11	**-.29**	.21	.01	.13	-.07	.00	-.16	-.07		**.31**	.22	**.27**
11. Extraversion	-.22	-.13	.03	**-.37**	**.37**	.20	-.21	-.01	**-.42**	.13		**.31**	.18
12. Openness	.18	.13	.37	.10	.11	.12	.07	**.59**	-.06	.02	-.04		.12
13. Conscientiousness	.08	.18	.16	**-.68**	.12	.17	**.38**	.23	-.23	.10	.21	.00	

Note. Bold values represent significant point-biserial and Pearson correlations ($p < .05$). Correlation coefficients for the Young-Updating group are above the diagonal, correlation coefficients for the Young-Binding group are below the diagonal. TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

Table C2

Correlation Coefficients of the Individual Differences for the Old-Mixed Group

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1. Age																											
2. Gender	-.04																										
3. Education	-.08	**-.48**																									
4. CFQ	-.01	.22	-.03																								
5. EPT	-.13	**-.33**	.22	.04																							
6. Motivation	.09	.01	**-.28**	**-.26**	-.04																						
7. Grit	-.06	**-.30**	.16	**-.41**	.03	-.04																					
8. TIS	.16	.09	**-.26**	.07	-.14	.09	.12																				
9. GSE	.07	-.09	.17	**-.30**	.02	.11	.19	.13																			
10. NFC	.05	-.20	.16	-.14	.10	.03	**.33**	**.26**	**.53**																		
11. Neuroticism	-.08	**.29**	**-.31**	**.43**	-.08	-.08	**-.39**	.01	**-.44**	**-.27**																	
12. Agreeableness	-.07	-.01	-.02	-.08	**.24**	.18	.18	-.03	-.03	.12	-.13																
13. Extraversion	.13	-.11	-.03	**-.37**	-.12	**.29**	**.29**	.14	**.42**	**.36**	**-.39**	.13															
14. Openness	-.16	**.28**	-.08	.14	.12	.00	-.02	.20	.12	**.40**	.07	**.31**	.14														
15. Conscientiousness	-.07	**-.24**	.11	**-.48**	-.04	.14	**.58**	.02	.22	**.27**	**-.40**	**.25**	**.31**	-.05													
16. Crafts	.08	**-.39**	.14	-.09	.13	-.13	.14	.04	.07	.05	.02	-.02	.08	-.14	.15												
17. Developmental activities	.13	-.14	**.30**	.01	.06	-.12	**.35**	.21	.12	.13	-.23	.20	**.25**	.14	.15	.12											
18. Experiential activities	.15	-.01	.07	-.06	.04	-.10	.15	.16	.17	.16	.02	**.29**	.20	**.30**	.18	**.31**	**.51**										
19. Game playing	.06	-.08	-.07	-.02	.10	.03	-.02	.08	.00	.00	.07	.01	-.02	.00	-.05	.22	-.05	.12									

20. Physical activities	-.09	.09	-.09	-.21	**-.26**	-.05	**.38**	**.25**	.07	.12	-.15	-.04	**.38**	.03	**.27**	**-.25**	**.25**	-.01	-.10								
21. Religious activities	.09	.01	-.03	-.01	-.22	.23	-.06	.00	.03	-.13	.04	-.06	**.30**	-.22	.12	.10	.12	.17	.04	.04							
22. Activities with social partner	-.01	.09	-.17	.01	-.04	-.04	.07	.01	.01	-.03	-.04	**.27**	.02	.14	.19	.11	**.31**	**.35**	.03	.18	-.05						
23. Public activities	.17	**-.39**	.06	-.01	.12	.01	.21	.22	.16	**.26**	-.23	.19	**.35**	.08	.06	**.28**	**.32**	**.57**	.09	.01	.12	.09					
24. Technology use	.02	-.18	.02	.15	.07	.10	.12	.20	-.01	.19	.20	**.26**	.05	.08	.23	.23	**.35**	**.35**	.15	.05	.19	**.30**	.23				
25. TV watching	.01	-.17	-.19	-.08	-.02	.10	-.02	.21	.07	-.04	.03	**-.27**	.02	-.07	.10	.02	-.11	-.10	.14	.01	.16	.16	-.03	.03			
26. Travel	-.08	-.05	-.08	-.12	.09	-.09	.20	.15	**.29**	**.29**	-.09	.01	.14	.23	.14	.03	.20	.22	.19	.08	.12	.21	.22	.09	.23		
27. Computer literacy	-.14	**-.24**	.11	-.11	.23	.17	.10	-.02	.17	.16	-.07	.12	.13	-.12	.21	-.03	.17	-.02	.12	-.01	-.06	-.10	.05	.24	.09	.08	
28. Training experience	.07	-.07	.19	.04	.03	-.20	.05	-.01	.05	.05	-.09	-.11	-.01	-.04	.03	.04	.08	-.08	.20	.07	.05	-.10	.01	.05	.04	.21	.21

Note. Bold values represent significant point-biserial, Spearman rank, and Pearson correlations ($p < .05$). CFQ = Cognitive Failure Questionnaire; EPT = Everyday Performance Test; TIS = Theorie of Intelligence; GSE = General Self-Efficacy scale; NFC = Need for Cognition.

Table C3

Nested Model Comparisons and Fit Indices for Baseline Latent Growth Curve Models For the First Four to Five Training Sessions

	χ^2	*df*	SRMR	CFI	Model comparison	$\Delta\chi^2$	Δdf
Young-Updating							
Model 1	**122.51**	8	.24	.65	-	-	-
Model 2	5.26	5	.05	1.00	1 vs. 2	**117.25**	3
Model 3	2.41	3	.03	1.00	2 vs. 3	2.84	2
Young-Binding							
Model 1	**195.65**	8	.56	.20	-	-	-
Model 2	6.12	5	.07	1.00	1 vs. 2	**189.52**	3
Model 3	3.65	3	.06	1.00	2 vs. 3	2.47	2
Old-Mixed							
Model 1	**129.04**	13	.18	.81	-	-	-
Model 2	**22.12**	10	.03	.98	1 vs. 2	**106.92**	3
Model 3	10.28	7	.01	.99	2 vs. 3	**11.84**	3

Note. Bold χ^2 values represent significant χ^2 statistics ($p < .05$). Model 2 (linear change in training performance) fitted the data from the Young-Updating and Young-Binding samples best, whereas Model 3 (non-linear change in training performance) fitted the data from the Old-Mixed sample best.

Table C4

Fit Indices for Baseline Latent Growth Curve Models for the First Four to Five Training Sessions and Bayes Factors for Variances and Covariances

	χ^2	df	SRMR	CFI	BF_{H1}	BF_{H0}
Young-Updating	5.26	5	0.05	1.00		
Covariance $_{\text{intercept, slope}}$	6.69	6	0.07	1.00	0.27	**3.69**
Variance $_{\text{intercept}}$	**115.77**	7	0.44	0.67	**> 100**	0.00
Variance $_{\text{slope}}$	**28.02**	7	0.13	0.94	**> 100**	0.00
Young-Binding	6.12	5	0.07	1.00		
Covariance $_{\text{intercept, slope}}$	7.25	6	0.07	0.99	0.22	**4.56**
Variance $_{\text{intercept}}$	**83.18**	7	0.35	0.67	**> 100**	0.00
Variance $_{\text{slope}}$	**35.41**	7	0.23	0.88	**> 100**	0.00
Old-Mixed	10.28	7	0.01	0.99		
Covariance $_{\text{intercept, slope}}$	13.12	8	0.07	0.99	0.50	1.99
Variance $_{\text{intercept}}$	**200.79**	9	0.49	0.69	**> 100**	0.00
Variance $_{\text{slope}}$	**41.30**	9	0.12	0.95	**> 100**	0.00

Note. Bold χ^2 values represent significant χ^2 statistics ($p < .05$). Bold BF values represent BF ≥ 3 indicating substantial to decisive evidence for the respective model. BF_{H1} represent BF favoring the alternative model, BF_{H0} represent BF favoring the null model.

Table C5

Associations of Individual Differences with the Change in Cognitive Performance Across the First Four to Five Training Sessions

	Young-Updating				Young-Binding				Old-Mixed			
Individual differences	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}
Demographic variables												
Age	-0.17	.261	0.24	**4.12**	-0.24	.104	0.44	2.26	-0.36	.004	**3.38**	0.30
Gender	0.21	.161	0.34	2.97	0.16	.293	0.21	**4.69**	0.32	.014	1.68	0.60
Real-world cognition												
Education	-	-	-	-	-	-	-	-	0.25	.081	0.49	2.04
CFQ	-	-	-	-	-	-	-	-	-0.17	.246	0.23	**4.28**
EPT	-	-	-	-	-	-	-	-	0.20	.161	0.31	**3.26**
Motivation	0.15	.324	0.21	**4.78**	0.05	.753	0.13	**7.61**	-0.07	.626	0.14	**7.33**
Cognition-related beliefs												
Grit	0.30	.059	0.74	1.35	0.01	.960	0.13	**7.99**	0.27	.057	0.64	1.56
TIS	-0.09	.595	0.15	**6.63**	0.01	.955	0.13	**7.99**	-0.44	.001	**10.37**	0.10
GSE	-0.12	.549	0.16	**6.37**	-0.04	.812	0.13	**7.78**	0.17	.284	0.21	**4.70**
EXSE	-0.03	.877	0.13	**7.53**	0.14	.349	0.19	**5.20**	-	-	-	-
NFC	0.19	.338	0.21	**4.85**	0.26	.107	0.44	2.27	0.06	.732	0.13	**7.78**
Personality												
Neuroticism	0.21	.183	0.31	**3.19**	0.06	.659	0.14	**7.26**	-0.24	.130	0.35	2.82
Agreeableness	-0.24	.130	0.41	2.41	-0.05	.696	0.13	**7.42**	0.11	.501	0.15	**6.59**
Extraversion	0.26	.129	0.40	2.53	-0.26	.069	0.56	1.78	-0.16	.310	0.20	**5.01**
Openness	-0.27	.060	0.60	1.66	-0.03	.837	0.13	**7.83**	-0.10	.514	0.15	**6.67**
Conscientiousness	-0.23	.116	0.42	2.37	0.10	.438	0.17	**5.96**	0.16	.338	0.19	**5.27**
Leisure activities												
Crafts	-	-	-	-	-	-	-	-	0.31	.043	0.83	1.21
Developmental activities	-	-	-	-	-	-	-	-	0.01	.965	0.12	**8.24**
Experiential activities	-	-	-	-	-	-	-	-	-0.33	.086	0.48	2.08
Game playing	-	-	-	-	-	-	-	-	0.00	.987	0.12	**8.24**
Physical activities	-	-	-	-	-	-	-	-	0.26	.069	0.57	1.76
Religious activities	-	-	-	-	-	-	-	-	-0.26	.057	0.65	1.53

Activities with social partner	-	-	-	-	-	-	-	-	-0.17	.283	0.21	**4.74**
Public activities	-	-	-	-	-	-	-	-	-0.02	.910	0.12	**8.19**
Technology use	-	-	-	-	-	-	-	-	0.23	.126	0.36	2.74
TV watching	-	-	-	-	-	-	-	-	-0.19	.198	0.27	**3.70**
Travel	-	-	-	-	-	-	-	-	0.28	.050	0.71	1.41
Computer/Training												
Computer literacy	-	-	-	-	-	-	-	-	-0.01	.948	0.12	**8.23**
Training experience	-	-	-	-	-	-	-	-	0.04	.790	0.13	**7.96**

Note. Bold values represent BF ≥ 3 indicating substantial evidence for the respective model. BF_{H1} represent BF favoring the alternative model, BF_{H0} represent BF favoring the null model. *b* = standardized estimates. CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test; TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

Table C6

Associations of Individual Differences with Baseline Cognitive Performance at the First Training Session

	Young-Updating				Young-Binding				Old-Mixed			
Individual differences	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}	*b*	*p*	BF_{H1}	BF_{H0}
Demographic variables												
Age	-0.11	.429	0.18	**5.61**	-0.18	.204	0.27	**3.70**	-0.24	.030	1.00	1.00
Gender	-0.03	.817	0.13	**7.41**	0.10	.488	0.16	**6.30**	0.37	<.001	**18.09**	0.06
Real-world cognition												
Education	-	-	-	-	-	-	-	-	0.20	.075	0.53	1.90
CFQ	-	-	-	-	-	-	-	-	0.00	.988	0.12	**8.25**
EPT	-	-	-	-	-	-	-	-	0.34	.002	**6.37**	0.16
Motivation	0.13	.308	0.22	**4.61**	0.19	.146	0.33	2.99	-0.14	.236	0.24	**4.20**
Cognition-related beliefs												
Grit	-0.09	.472	0.17	**5.90**	0.27	.043	0.76	1.31	0.31	.006	**3.08**	0.32
TIS	-0.38	.002	**5.35**	0.19	0.17	.250	0.24	**4.21**	0.04	.736	0.13	**7.79**
GSE	0.04	.784	0.14	**7.33**	-0.06	.665	0.14	**7.29**	-0.39	.001	**7.03**	0.14
EXSE	0.14	.295	0.22	**4.48**	0.17	.200	0.27	**3.65**	-	-	-	-
NFC	0.18	.254	0.25	**4.08**	-0.03	.841	0.13	**7.84**	0.10	.464	0.16	**6.33**
Personality												
Neuroticism	-0.08	.589	0.15	**6.59**	-0.03	.837	0.13	**7.83**	-0.21	.097	0.44	2.26
Agreeableness	-0.13	.376	0.19	**5.20**	0.31	.007	2.42	0.41	0.19	.107	0.41	2.42
Extraversion	0.04	.821	0.13	**7.42**	-0.09	.525	0.15	**6.55**	-0.41	<.001	**18.95**	0.05
Openness	0.06	.659	0.14	**6.91**	0.12	.311	0.20	**4.89**	-0.04	.709	0.13	**7.69**
Conscientiousness	-0.08	.585	0.15	**6.57**	-0.06	.648	0.14	**7.21**	0.27	.026	1.12	0.90
Leisure activities												
Crafts	-	-	-	-	-	-	-	-	0.21	.100	0.43	2.32
Developmental activities	-	-	-	-	-	-	-	-	0.29	.036	0.89	1.13
Experiential activities	-	-	-	-	-	-	-	-	-0.26	.111	0.40	2.49
Game playing	-	-	-	-	-	-	-	-	0.06	.606	0.14	**7.23**
Physical activities	-	-	-	-	-	-	-	-	-0.10	.412	0.17	**5.92**
Religious activities	-	-	-	-	-	-	-	-	-0.26	.023	1.21	0.83

Activities with social partner	-	-	-	-	-	-	-	-	-0.02	.884	0.12	**8.16**
Public activities	-	-	-	-	-	-	-	-	0.24	.090	0.46	2.16
Technology use	-	-	-	-	-	-	-	-	-0.03	.841	0.12	**8.08**
TV watching	-	-	-	-	-	-	-	-	0.10	.414	0.17	**5.94**
Travel	-	-	-	-	-	-	-	-	-0.10	.407	0.17	**5.88**
Computer/Training												
Computer literacy	-	-	-	-	-	-	-	-	0.17	.157	0.31	**3.20**
Training experience	-	-	-	-	-	-	-	-	0.17	.165	0.30	**3.31**

Note. Bold values represent BF ≥ 3 indicating substantial to strong evidence for the respective model. BF_{H1} represent BF favoring the alternative model, BF_{H0} represent BF favoring the null model. *b* = standardized estimates. CFQ = Cognitive Failure Questionnaire; EPT = Everyday Problems Test; TIS = Theories of Intelligence; GSE = General Self-Efficacy scale; EXSE = Self-Efficacy to Regulate Exercise scale; NFC = Need for Cognition.

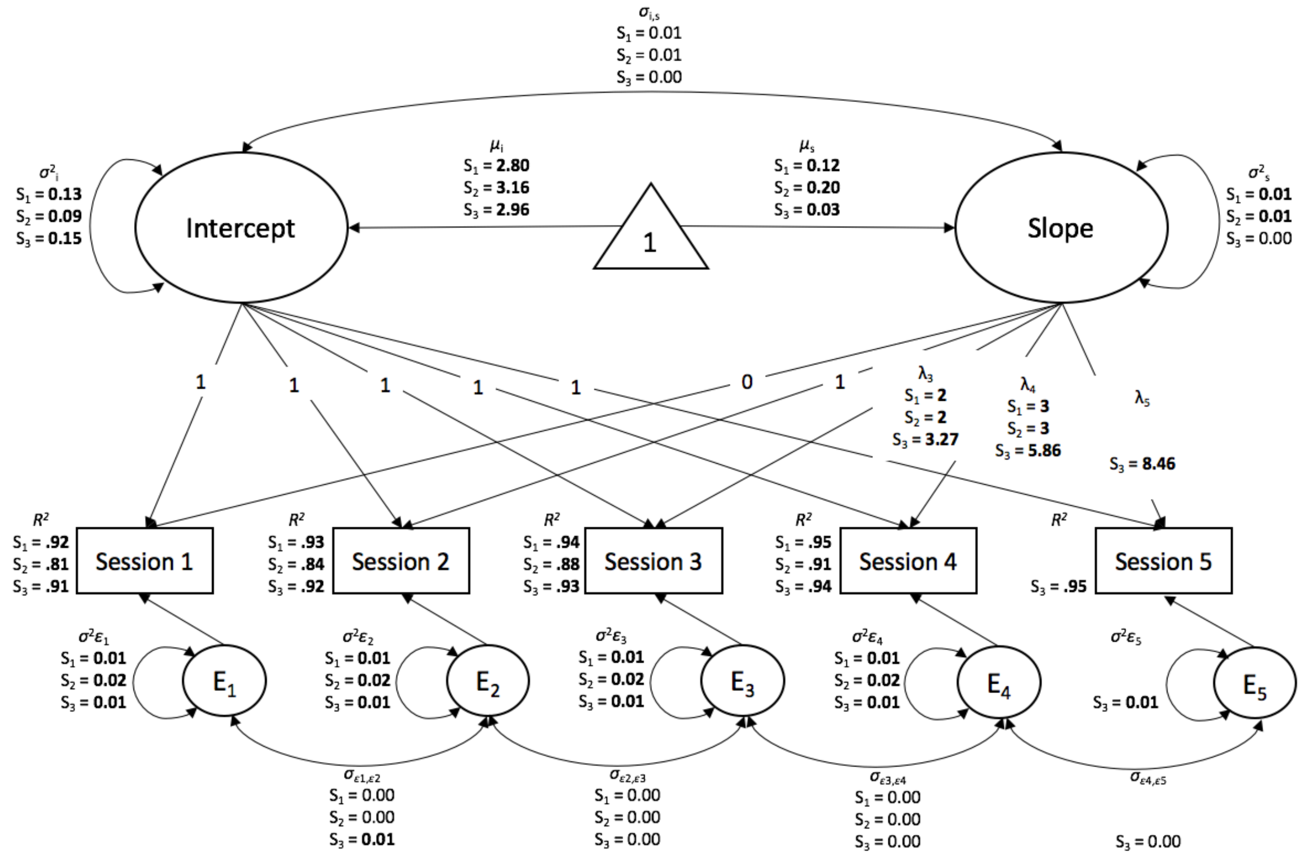

Figure C13. Latent baseline model of change in training performance for the first four to five training sessions, linear growth curve models for the Young-Updating and Young-Binding groups and non-linear growth curve model for the Old-Mixed group. As the first training block consisted of only four training sessions in the younger adults, pattern coefficients, error terms, and error variances were not estimated for session 5. Estimated mean levels of training performance for the Young-Updating group are 2.80 (session 1), 2.92 (session 2), 3.04 (session 3), and 3.16 (session 4), for the Young-Binding group 3.16 (session 1), 3.36 (session 2), 3.56 (session 3), and 3.76 (session 4), and for the Old-Mixed group 2.96 (session 1), 2.99 (session 2), 3.06 (session 3), 3.14 (session 4), 3.21 (session 5).[4] Bold numbers indicate significance ($p < .05$). Unstandardized estimates are presented

[4] Estimated means are determined by the factor mean of the intercept μ_i and pattern coefficients λ and were computed by the formula: estimated mean = $\mu_i + \lambda * \mu_s$ (see Kline, 2016 for details).

for the Young-Updating sample (S_1), the Young-Binding sample (S_2), and the Old-Mixed sample (S_3). Squares represent observed variables (training sessions 1 to 5), circles represent latent factors, and the triangle is modeled to represent the means of the latent factors (μ_i = mean of the intercept, μ_s = mean of the slope). $\sigma^2{}_i$ = variance of the intercept; $\sigma^2{}_s$ = variance of the slope; $\sigma_{i,s}$ = covariance of intercept and slope; $\lambda_{3\text{-}5}$ = pattern coefficients; $E_{1\text{-}5}$ = error terms; $\sigma^2\varepsilon_{1\text{-}5}$ = error variances; $\sigma_{\varepsilon,\varepsilon}$ = error covariances

7 GENERAL DISCUSSION

The main goal of this thesis was to investigate the effects of an engaged lifestyle and a cognitive training intervention on cognition in healthy older adults. More specifically, the present thesis has addressed three major topics: the association between an engaged lifestyle and functional ability in everyday life, while considering cognitive ability (i.e., WM) as one underlying mechanism (Article I), the effectiveness of cognitive training interventions in older adults (Articles II and III), and the influence of individual differences on cognitive plasticity in both younger and older adults (Article IV). In this chapter, the main findings will first be briefly summarized and then discussed with regards to their theoretical, methodological, and practical implications. Thereafter, future directions for cognitive training studies will be proposed, including the application of measurement models of WM to understand the cognitive processes that occur during the training intervention, the inclusion of within-person covariates to determine the optimal context for training progress, and the assessment of transfer in real-life settings.

7.1. SUMMARY

In the first article of this thesis (see Chapter 3 – *Functional ability in everyday life: Associations with an engaged lifestyle are mediated by working memory*), we examined the association between an engaged lifestyle, assessed via leisure activities, and functional ability in everyday life in older adults, while considering WM ability as a potential mediator of this association. We used two indicators of functional ability in everyday life, namely self-reported and objective everyday performance. Using a latent-variables approach we found that WM fully mediated the association between an indicator of intellectual activities (i.e., game playing) and objective functional ability in everyday life. In addition, we found a negative relation between physical activities and self-reported failures in everyday life, which was, however, not mediated through WM. Thus, the results from this study indicate that an engaged lifestyle (i.e., intellectual and physical activities) is related to functional ability in everyday life and that WM is one mechanism by which intellectual activity may be related to objective functional ability in everyday life.

In the second article of this thesis (see Chapter 4 – *Plasticity in different age groups: Adult lifespan*), we reviewed the evidence for cognitive training effectiveness in older adults. We found that training gains tend to be of small to moderate magnitude compared to no training both on the behavioral and the brain level, but are small or disappear when compared to active control conditions. Across the different types of training interventions, mainly near transfer effects of small to moderate size have been documented. Based on the existing literature, we argued that apart from methodological and design-related improvements, transferring standardized, lab-based training interventions and transfer assessment into real life is one of the most challenging endeavors for future training research. Moreover, we concluded that future research should further investigate the role of individual differences and time-varying covariates to facilitate the development of individually tailored interventions.

In the third article of this thesis (see Chapter 5 – *Working memory training in older adults: Bayesian evidence supporting the absence of transfer*) we investigated the effectiveness of a WM training intervention in a relatively large sample of older adults while considering study design (e.g., active control group, assessment on the level of abilities instead of single tasks) and data-analytical issues that are prevalent in the field. Using Bayesian inference, we were able to show that participants largely improved on the trained WM tasks, but that those gains neither transferred to untrained and similar WM tasks nor untrained but related cognitive abilities such as intelligence, shifting or inhibition. Thus, we conclude that WM training is, at the moment, not an effective approach to improve general cognitive functioning in older adults.

In the fourth article of this thesis (see Chapter 6 – *Do individual differences predict change in training performance: A latent growth curve modeling approach*), we aimed to identify individual differences variables predictive of baseline cognitive performance and change in training performance across three samples of younger and older adults. We included a variety of individual differences variables that have previously been discussed in the literature, such as personality, motivation or cognition-related beliefs. Interestingly, we found that those individual differences variables were largely unrelated to change in training performance across all samples. Only baseline cognitive performance was related to change in training performance in the younger samples, with those starting on a higher baseline performance level showing larger training gains (i.e., magnification effect). Thus, our findings suggest that it is unlikely that individually-tailored training interventions based on the frequently proposed between-person variables such as personality or motivation tested in this study would boost training performance to a meaningful degree.

Taken together, the studies included in this thesis helped to gain further insight into the associations between leisure activities and cognitive ability as well as functional ability in everyday life, and the effect of a targeted WM training intervention on cognitive plasticity across a range of cognitive abilities. Further, this thesis comprehensively examined the effect of 29 moderators on the trainability of cognitive performance in both younger and older adults.

7.2. Implications

7.2.1. Theoretical Implications

This thesis provides evidence that an intensive, multi-paradigm WM training intervention leads to improved performance on the trained WM tasks. However, there was also substantial evidence for the absence of the generalization of training gains to untrained WM tasks (i.e., near transfer) and related cognitive abilities, including shifting, inhibition, and fluid intelligence (i.e., far transfer).

Theoretically, two processes can underlie training-induced transfer to untrained tasks or abilities: (a) an expansion of WM capacity or (b) enhancements in WM efficiency (von Bastian & Oberauer, 2014). Von Bastian and Oberauer (2014) argue that expansions in WM capacity are expected if the trained and the transfer tasks share the same underlying processes, and if these processes are effectively being targeted during the WM intervention. Thus, cognitive improvements caused by expanded WM capacity are assumed to manifest relatively independent of the stimulus material and the structure of the transfer tasks. In turn, enhancements in WM efficiency, that is, the more efficient use of the pre-existing WM capacity, is assumed to lead to improvements only on tasks that are highly similar to the trained tasks with regard to stimulus material and structure. Performance improvements based on enhanced WM efficiency are likely to be the cause of skill acquisition, such as strategy-use or the automatization of basic processes.

Given the highly specific improvements on the trained tasks found in Article III of this thesis, it is likely that individuals have acquired task-specific knowledge that is not transferable to untrained stimulus material and structurally dissimilar tasks. Thus, this pattern of results, especially the absence of near transfer effects to WM, tentatively indicates that enhancements in WM efficiency rather than expansions of WM capacity were more likely to have occurred during the intervention. Unfortunately, strategy-use during the intervention was not assessed in the study and thus, potential mediator effects of strategy-use could not be further investigated in the individual differences analysis (Article IV) of this thesis.

7.2.2. Methodological Implications

Together with others (e.g., Clark et al., 2017; Dougherty et al., 2016; Sprenger et al., 2013; von Bastian et al., in press) we were some of the first researchers to use the Bayesian approach to investigate if cognitive training is effective. We argue that the application of the Bayesian approach will advance the cognitive training field not only by providing more differentiated information about the states of evidence compared to traditional NHST (cf. Dienes & Mclatchie, 2017), but also by facilitating the publication of null effects and thus counteract publication bias.

Publication bias refers to the phenomenon that studies reporting significant effects are much more likely to get published compared to studies reporting null effects, and is a well-documented problem in psychology and related research fields since over half of a century now (e.g., Sterling, 1959). Nevertheless, there is an increasing trend in frequency of published studies reporting positive support for the tested hypothesis (as compared to null effects), and this trend is one of the strongest in the field of psychology and psychiatry (Fanelli, 2011). Besides the mere importance of publishing null results, for instance in intervention research, publication bias can be a serious threat to the conclusions of systematic reviews and meta-analyses. As reviews and meta-analyses often only rely on published studies, they potentially overestimate the effect under study and can skew the conclusions towards positive effects (cf. Thornton & Lee, 2000).

One potential reason for the difficulty to publish null results might be shortcomings within the NHST framework, as it is ill-suited to falsify a theory under study and thus confirm the null hypothesis (cf. Konijn, van de Schoot, Winter, & Ferguson, 2015). Therefore, Konijn et al. (2015) have proposed to use Bayesian statistics, as the Bayesian framework allows to find statistical support for the null hypothesis by directly comparing the null to an alternative hypothesis. Thus, in a field, such as the cognitive training intervention research, where null results are of equal practical and theoretical importance as positive effects, the use of adequate statistical methods (i.e., Bayesian statistic) to accumulate evidence not just for the alternative, but also for the null hypothesis, may potentially increase the likelihood to publish null results and might lead to more accurate conclusions in systematic reviews and meta-analyses. Pre-registration and transparent research practices (e.g., sharing data and analyses scripts through platforms such as the Open Science Framework) further diminish publication bias.

7.2.3. Practical Implications

The so-called “brain-training” industry has boomed in recent years and people are investing their time and money in programs or apps that promise to improve their intelligence and boost their general cognitive functioning. One possible reason for this boom is the prominent study from Jaeggi et al. (2008) in which they showed that WM training leads to improvements in intelligence in younger adults. The study has received massive attention in the media and the cognitive training field, however, other research groups have failed to find improvements in intelligence after WM training (e.g., Harrison et al., 2013; Redick et al., 2013). Thus, the question of whether or not such interventions are effective and worth the time and money has long been a matter of debate in the cognitive training field. However, because of severe methodological shortcomings of many studies in the field (e.g., small samples, transfer assessment on the level of individual tasks, passive control groups), it was difficult to conclusively settle this debate. Using a rigorous study design addressing these shortcomings, and by applying adequate statistical procedures, we were able to show that WM training in older adults is ineffective in terms of generating transfer to highly similar WM tasks and related cognitive abilities such as intelligence. Thus, we cannot, at the moment, recommend WM training as an effective means to improve general cognition beyond the specifically trained tasks.

This recommendation is in line with a position statement that was published by the Stanford Center of Longevity and the Max Planck Institute of Human Development and signed by over 70 researchers from the cognitive training or related fields ("A Consensus on the Brain Training Industry From the Scientific Community", 2014). They also

> *“[…] object to the claim that brain games offer consumers a scientifically grounded avenue to reduce or reverse cognitive decline when there is no compelling scientific evidence to date that they do. The promise of a magic bullet detracts from the best evidence to date, which is that cognitive health in old age reflects the long-term effects of healthy, engaged lifestyles. In the judgment of the signatories below, exaggerated and misleading claims exploit the anxieties of older adults about impending cognitive decline. We encourage continued careful research and validation in this field.”*

Although the investigation of long-term effects of an engaged lifestyle on cognition was not part of this thesis, we found positive, cross-sectional associations between an engaged lifestyle, more specifically, intellectual and physical activities with cognitive ability and functional ability in old age (Article I). Thus, in order to maintain high levels of everyday functioning and cognitive performance in old age, a stimulating everyday life including intellectual and physical engagement may seem to have greater potential than current training interventions.

7.3. FUTURE DIRECTIONS

The main question of this thesis was to investigate if an engaged lifestyle and cognitive training positively impact cognitive ability, cognitive plasticity and functional ability in everyday life, and to what extent these associations are moderated or mediated by individual differences variables. Thus, returning to the central question of this thesis, future cognitive training studies should focus on the following three aspects: (1) The investigation of the cognitive processes (and the changes thereof) that occur during training interventions to improve the understanding of the mechanisms and boundaries of WM plasticity, (2) the identification of the optimal training context by including within-person covariates of cognitive performance, and (3) the assessment of transfer in real-life settings to quantify benefits for everyday cognition and functional ability in everyday life.

7.3.1. TACKLING COGNITIVE PROCESSES DURING TRAINING

As theoretically proposed by von Bastian and Oberauer (2014), transfer to untrained cognitive tasks and abilities is expected if the intervention leads to expansions in WM capacity, as opposed to efficiency enhancements of pre-existing WM capacity. The results presented in this thesis challenge the idea that WM capacity can be expanded through cognitive training, as indicated by the absence of near transfer to untrained WM tasks. Thus, in order to develop training interventions that generate transfer to untrained cognitive tasks and abilities, it is crucial to first understand the cognitive processes (and the potential mechanisms of WM plasticity) that occur during the intervention.

As of yet, researchers are primarily interested in the question of whether cognitive training leads to (far) transfer effects, however, at the expense truly understanding what happens during the intervention itself. One possibility to tackle the cognitive processes during WM training interventions are sophisticated measurement models for WM tasks, which are currently being developed (e.g., Memory Measurement Models M3; Oberauer & Lewandowsky, submitted). By applying these measurement models to the WM training tasks, it is possible to capture the processes affecting cognitive performance over time (e.g., encoding, filtering), yielding a more fine-grained picture of training-induced changes in cognitive processing.

7.3.2. Further Predictors and Covariates of Training Performance

Although we found large individual differences in change in training performance, our data provided evidence against between-person variables such as demographics (e.g., age and gender), dispositions (e.g., personality, motivation or cognition-related beliefs) and behaviours (e.g., computer usage, leisure activities) predicting these training gains. Only baseline cognitive performance was associated with change in training performance, and was so inconsistently across the included samples.

However, aside from merely focusing on between-person differences in change in cognitive performance, it might be worthwhile to take a closer look at the variability of cognitive performance. It is known that cognitive performance reliably fluctuates from day-to-day and at faster timescales (Schmiedek et al., 2013). The term intraindividual variability (IIV) in cognitive performance (e.g., reaction times, or accuracy) refers to transient, relatively short-term fluctuations in cognitive functioning. It has been argued that increased IIV in cognitive performance may be related to neurobiological changes that occur as a consequence of aging and disease (Li & Lindenberger, 1999, but see Schmiedek et al., 2013). Indeed, (increased) IIV in cognitive performance has found to be positively correlated with age, associated with lower levels of cognitive performance, and to be consistent across cognitive abilities, and different domains (e.g., cognitive and physical performance; see Hultsch & McDonald, 2004 for an overview). Further, increased IIV in cognitive performance is associated with maladaptive real-life outcomes, such as lower lifestyle engagement (Bielak et al., 2007) and lower cognitive status in old age (Bielak, Hultsch, Strauss, MacDonald, & Hunter, 2010; Hultsch, MacDonald, Hunter, Levy-Bencheton, & Strauss, 2000). Further, Garrett, MacDonald, and Craik (2012)(Garrett et al., 2012) recently showed that IIV in cognitive performance can be experimentally reduced by providing goal-directed feedback during a learning situation in both younger and older adults. Thus, (a) including IIV in cognitive training performance as between-person predictor and (b) assessing within-person covariates of IIV in cognitive training performance (e.g., daily activities, daily stress) may contribute to the understanding of who benefits from cognitive training.

Between-Person Differences in IIV in Cognitive Training Performance

Although somewhat at odds with the above-mentioned literature, in the context of learning, IIV in cognitive performance may reflect an adaptive rather than a maladaptive process. Two studies found that increased IIV in cognitive performance is positively related to practice gains in a cognitive dual-task paradigm (Strobach, Gerstorf, Maquestiaux, & Schubert, 2015), and in speed, memory, and reasoning tasks (Allaire & Marsiske, 2005). The authors argue that increased IIV in cognitive performance may reflect the flexible use and variation of different strategies in early stages of task acquisition in order to improve performance. Thus, investigating whether between-person differences in IIV in cognitive performance (and thus flexibility in task learning) are associated with training and transfer gains in the context of WM training could not only shed light on the understanding of who benefits from WM training, but also on the generalizability of the previous findings regarding IIV in cognitive performance as a predictor of cognitive learning to WM interventions.

Within-Person Covariates of IIV of Cognitive Training Performance

The technological advancements in the recent years allow to easily assess psychological processes in naturalistic environments (i.e., ambulatory assessment). Thus, instead of focusing solely on between-person predictors of cognitive performance, we and others (e.g., Könen & Karbach, 2015) argue that to advance the cognitive training field, a special emphasis should be placed on within-person covariates of cognitive training performance. Investigating under which circumstances and in which contexts cognitive performance can be enhanced for each and every individual may constitute a breakthrough with regards to the tailoring of cognitive training.

There is accumulating research that reports within-person couplings of cognitive performance fluctuations and other internal or external variables. For instance, the group around Sliwinsky and Stawski investigated how IIV in daily stress is related to daily cognitive performance in older adults. They found associations between indicators of daily stress and reaction-time variability during attention-demanding cognitive tasks (Sliwinski, Smyth, Hofer, & Stawski, 2006), as well as variability in cognitive interference (Stawski, Mogle, & Sliwinski, 2011). Further, Brose and colleagues found that, in younger adults, daily WM performance was positively associated with daily positive affect and motivation, and negatively associated with daily negative affect (Brose et al., 2012; Brose, Lövdén, & Schmiedek, 2014). Investigating within-person couplings between sleep and WM performance in children, Könen, Dirk, and

Schmiedek (2015) found that tiredness was associated with impaired WM performance in the afternoon, and sleep quality as well as time spent in bed were associated with WM performance the next day. Finally, indicators of an engaged lifestyle, namely daily social activities, have shown to be related to daily cognitive performance (i.e., episodic memory) in older adults (Bielak, Mogle, et al., 2017).

Thus, the comprehensive assessment of daily internal (e.g., motivation, affect, sleep parameters) and external factors (e.g., stressors, leisure activities, environments) that are assumed to co-vary with daily cognitive performance may further contribute to understand the underlying mechanisms of training performance. Further, based on recent technological advancements in mobile sensor devices, these internal and external factors can easily be assessed using a multi-modal assessment toolbox including, among others, tracking technologies to objectively assess physical activity (e.g., GPS, accelerometer), physiological parameters (e.g., sleep, heart rate), or devices to record social interactions (e.g., EAR; Mehl et al., 2001).

7.3.3. Transfer Assessment in Real-Life

Although the ultimate goal of cognitive training interventions is the enhancement of meaningful real-life outcomes such as cognitive functioning in real-life settings or functional ability in everyday life, cognitive training studies have primarily focussed on the assessment of transfer to traditional lab-based measures of cognitive ability and the ecologically valid assessment of transfer to measures of functional ability or everyday cognition has often been neglected (but see Ball, Edwards, Ross, & McGwin, 2010; Cantarella et al., 2017; Willis et al., 2006 for exceptions).

Everyday cognition is defined as the use of fundamental cognitive abilities (e.g., WM) and task-specific knowledge to solve complex everyday problems in naturalistic contexts (Gamaldo & Allaire, 2016). Although lab-based measures of everyday cognition (e.g., EPT) have shown to be strongly related to lab-based measures of basic cognitive abilities (e.g., Willis, Jay, Diehl, & Marsiske, 1992), there is a perceived disconnection between the studies reporting an age-related decline in basic cognitive functioning and the observation in real-life that older adults report high levels of life satisfaction (e.g., Lachman, Röcke, Rosnick, & Ryff, 2008; Scheibe & Carstensen, 2010), and clearly manage their activities of daily life successfully. Thus, assessing transfer not only in context-free environments to lab-based measures of maximum cognitive performance, but embedding key areas of cognitive training evaluation into real-life contexts by investigating everyday cognition (Bielak, Hatt, & Diehl, 2017; Verhaeghen et al., 2012) is an important endeavour of future training research to better understand the value of cognitive training for the everyday lives of older adults.

However, self-report measures (e.g., IADL; Lawton & Brody, 1969; CFQ; Broadbent et al., 1982), and performance-based, but measures of everyday cognition in the lab (EPT; Willis & Marsiske, 1993) arguably do not capture the complex requirements and demands, and the richness of real-life situations. Thus, objective and ecologically valid measures of everyday cognition that can be directly implemented in natural real-life settings are needed. One example of such a measure is an adapted real-world version of the What-Where-When task assessing episodic memory performance (Mazurek et al., 2015). During the two rounds of the task, which take place approximately two hours apart, participants have to hide everyday objects at pre-defined locations in a cluttered office room. Two hours after the second round, participants then have to recall what (i.e., the object) they hid where (i.e., the location) and when (i.e., during the first or second round).

Other possibilities to assess everyday cognition in real-life settings include driving competence or medication-taking behavior (see Bielak, Hatt, et al., 2017 for an overview), or the evaluation of text and language comprehension, a domain of everyday cognition which is strongly related basic cognitive processes such as WM (e.g., Feldman Barrett et al., 2004). Reading can easily be assessed in real-life contexts and further complemented by applying eye tracking methodology to tackle the cognitive processes underlying text comprehension (Raney, Campbell, & Bovee, 2014). A number of gaze metrics can be used to study cognitive processes, including fixations (reflecting the time needed to process a stimulus), voluntary or involuntary saccades (reflecting shifts in attention), accuracy/latency of saccades (reflecting cognitive control capacity), and scan path (reflecting the analysis of complex (series of) stimuli such as during reasoning tasks; see e.g., Eckstein, Guerra-Carrillo, Miller Singley, & Bunge, 2017 for an overview). Thus, using eye tracking devices may not only provide information regarding the underlying mechanisms of solving transfer tasks, but are also applicable to real-life contexts to ensure ecological validity. Similar approaches are currently being tested in personality research, where eye movements are used to assess manifestations of personality traits during a real-life shopping task (Aschwanden, Langer, & Allemand, in preparation).

7.4. CONCLUDING REMARKS

The empirical studies in this thesis provide evidence that an engaged lifestyle is related to both cognitive ability and functional ability in everyday life, and that the associations between intellectual activities and objective functional ability in everyday life is mediated through cognitive ability. We found, however, evidence that a WM training intervention does not enhance general cognitive functioning in older adults and that individual differences do not moderate training effectiveness in both younger and older adults, except for baseline cognitive ability in younger adults. Thus, given these results, cognitive training interventions are currently not an effective means to enhance general cognitive functioning, and older individuals should rather engage in an active lifestyle consisting of intellectual and physical activities. Future studies should investigate the cognitive processes underlying cognitive plasticity during training intervention and identify within-person covariates of cognitive performance to further understand the mechanisms of and the optimal context for cognitive plasticity. Further, transfer effects to everyday cognition and functional ability in everyday life should be assessed in real-life settings.

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EDUCATION

2014 – 2018 **PhD student**, University of Zurich, Switzerland (summa cum laude)
URPP "Dynamics of Healthy Aging"

PhD thesis: *Cognition in old age: The effect of leisure activities and training interventions* [Advisors: Prof. Dr. Mike Martin, Prof. Dr. Klaus Oberauer]

LIFE fellow at the International Max Planck Research School, The Life Course: Evolutionary and Ontogenetic Dynamics

Joint international PhD program of the Max Planck Institute for Human Development, Freie University Berlin, Humboldt University zu Berlin, University of Michigan, University of Virginia, and University of Zurich

2014 **M.Sc. in Psychology,** University of Zurich, Switzerland (summa cum laude)

Master thesis: *Targeting object-location memory in older adults: Behavioural and neural changes after a process-based cognitive training intervention*
[grade: excellent; Advisor: Prof. Dr. Mike Martin]

2011 **B.Sc. in Psychology**, University of Zurich, Switzerland

Bachelor thesis: *Experience-dependent and training-induced neuroplasticity across the lifespan* [grade: excellent; Advisor: Prof. Dr. Lutz Jäncke]

ACADEMIC APPOINTMENTS

2018 **Scientific project developer and manager (100%),** University of Zurich, Switzerland,
URPP "Dynamics of Healthy Aging"
Senior University of Zurich

2017 – 18	**Scientific project manager (20%),** University of Zurich, Switzerland URPP "Dynamics of Healthy Aging" Senior University of Zurich
2014 – 18	**Predoctoral researcher,** University of Zurich, Switzerland URPP "Dynamics of Healthy Aging" Project leader of the "**Healthy Cognitive Aging and Plasticity (h-CAP)**" study A large-scale study on the effects of an engaged lifestyle and cognitive training on cognitive ability and plasticity in old age
2016 /5 weeks	**Visiting predoctoral researcher,** Humboldt University zu Berlin, Germany Emmy Noether Research Group "Adaptation to Major Life Events" Working with Dr. Annette Brose
2015 /4 weeks	**Visiting predoctoral student** at the University of Colorado Boulder, USA Department of Cognitive Psychology and Cognitive Neuroscience Working with Prof. Dr. Akira Miyake and Dr. Claudia von Bastian
2010 – 13	**Research assistant**, University of Zurich, Switzerland Cognitive Psychology Unit Normal Aging and Plasticity Imaging Center (INAPIC) Developmental Psychology: Infancy and Childhood Unit Gerontopsychology and Gerontology Unit Social and Business Psychology Unit

FORTHCOMING PUBLICATIONS

Guye, S., Röcke, C., Martin, M., & von Bastian, C. C. (in preparation). *Everyday life competence: Associations with engaged lifestyle are mediated by working memory.*

Oschwald, J., **Guye, S.,** Liem, F., Rast, P., Willis, S., Röcke, C., Jäncke, L., & Martin, M., & Mérillat, S. (in preparation). *Brain structure and cognitive ability in healthy aging: A review on longitudinal correlated change.*

PEER-REVIEWED PUBLICATIONS

von Bastian, C. C., **Guye, S**., & De Simoni, C. (in press). How strong is the evidence for the effectiveness of working memory training? In M. F. Bunting, J. M. Novick, M. R. Dougherty & R. W. Engle (Eds.), *Cognitive and Working Memory Training: Perspectives from Psychology, Neuroscience, and Human Development*. New York, NY: Oxford University Press.

Guye, S., & von Bastian, C. C. (2017). Working memory training in older adults: Bayesian evidence supporting the absence of transfer. *Psychology and Aging, 32(8),* 732–746, doi:10.1037/pag0000206

Guye, S., De Simoni C., & von Bastian, C. C. (2017). Do individual differences predict change in cognitive training performance? A latent growth curve modelling approach. *Journal of Cognitive Enhancement, 1*(4), 374–393, doi:10.1007/s41465-017-0049-9

Guye, S., Röcke, C., Mérillat, S., von Bastian, C. C., & Martin, M. (2016). Plasticity in different age groups: Adult lifespan. In T. Strobach & J. Karbach (Eds.), *Cognitive Training: An Overview of Features and Applications* (pp. 45 – 55). Berlin: Springer.

RESEARCH GRANTS

2016 PI: "Healthy aging from lab to life: Determining the connections between lab-based cognitive abilities and real-life activities"
Forschungskredit of the University of Zurich for doctoral students

2016 "Personality, cognition, and leisure activities in old age"
Competitive intramural funding from the Jacobs Foundation

2015 Presentation coaching for the LIFE fellows in Zurich
Competitive intramural funding from the Jacobs Foundation

2015 "Affect and cognition"
Competitive intramural funding from the Jacobs Foundation

2014 PI: „Individual differences in working memory training with older adults"
Suzanne and Hans Biäsch Foundation for Applied Psychology

TRAVEL GRANTS

2017 International Conference Aging and Cognition in Zurich, Switzerland
Grant of the Faculty of Arts and Social Science for the University of Zurich

2017 European Conference of Psychology in Amsterdam, The Netherlands
Travel grant of the Faculty of Arts and Social Science for the University of Zurich

2017 European Conference of Psychology in Amsterdam, The Netherlands
Travel grant of the SAGW

2016 Invitation to the COGITO Conference 2016, Max-Planck Institute for Human Development in Berlin, Germany

2016 Gerontological Society of America Annual Meeting 2016 in New Orleans, USA,
Travel grant of the Faculty of Arts and Social Science of the University of Zurich

2016 Gerontological Society of America Annual Meeting 2016 in New Orleans, USA,
Travel grant from the Department of Psychology of the University of Zurich

2015 LIFE Academy in Ann Arbor, USA
Travel grant of the Faculty of Arts and Social Science for the University of Zurich

AWARDS

2016 Poster Award at the SGG SSG Conference, Fribourg, Switzerland

TALKS (* presenting author)

Guye, S*. (2017, December). *Cognitive training in adulthood: From hype to reality.* Invited talk at colloquium of developmental psychology of the the Max-Planck Institute of Human Development in Berlin, Germany

Guye, S.*, De Simoni, C., & von Bastian, C. C. (2017, October). *Working memory training effectiveness and the role of individual differences.* Talk the LIFE Fall Academy in Zurich, Switzerland.

Guye, S.*, De Simoni, C., & von Bastian, C. C. (2017, April) *Predicting trainability in younger and older adults using latent growth curve modeling.* Invited symposium talk at the European Congress of Psychology, Amsterdam, The Netherlands.

Guye, S.*, De Simoni, C., & von Bastian, C. C. (2017, March) *Predicting training performance in older adults: Who improves the most?* Invited key note talk at 4th International Conference Aging and Cognition, Zurich, Switzerland.

von Bastian, C. C.*, De Simoni, C., & **Guye, S.** (2017, March). *No evidence for transfer effects after process-based working memory training.* Talk at the Tagung experimentell arbeitender Psychologen (TeaP), Dresden, Germany.

Guye, S.*, von Bastian, C. C., Röcke, C., & Martin, M. (2016, November) *Does personality predict working memory training performance?* Invited symposium talk at the Gerontological Society of America Annual Meeting, New Orleans, USA.

Guye, S.* (2015, December). *Geistige Fitness im Alter.* Talk for the participants of the h-CAP study to report preliminary findings, University of Zurich, Switzerland.

Guye, S.* (2015, July). *Working memory training in older age. Do individual differences predict training effectiveness?* Invited talk at the colloquium of Prof. Akira Miyake, Department of Cognitive Psychology and Cognitive Neuroscience, University of Colorado Boulder, USA.

POSTER PRESENTATIONS (* presenting author)

Guye, S.*, Röcke, C., & Martin, M., & von Bastian, C. C. (2017, November). *Everyday Competence: Associations with an Engaged Lifestyle and the Mediating Role of Working Memory.* Poster presented at the URPP Dynamics of Healthy Aging In-House Conference, Ittingen, Switzerland.

Guye, S.*, von Bastian, C. C., Röcke, C., & Martin, M. (2017, August). *Working memory training in old age: The role of individual differences.* Poster presented at the WHO Site Visit at the URPP Dynamics of Healthy Aging, Zurich, Switzerland.

Guye S.*, von Bastian, C. C., Röcke, C., & M. Martin (2016, May). *Working memory training in old age: The role of individual differences.* Poster presented at the LIFE Spring Academy, Charlottesville, United States.

Schwager, D.*, **Guye, S.**, & Martin, M. (2016, May). *Personality, cognition, and leisure activities in old age: The role of social, physical, and mental activities in the relationship between the Big Five and working memory.* Poster presented at the Masterstudierenden und Doktorierenden-Kongress (MaDoKo), Zurich, Switzerland.

Guye, S.*, von Bastian, C. C., Röcke, C., & Martin, M. (2016, January). *The effectiveness of a working memory training in healthy older adults: Preliminary results.* Poster presented at the SGG SSG Conference, Freiburg, Switzerland.

Guye, S.*, von Bastian, C. C., Röcke, C., & Martin, M. (2015, October). *Is working memory training effective in older adults: Preliminary results.* Poster presented at the LIFE Fall Academy, Öhningen, Germany.

Guye, S.*, von Bastian, C. C., Costa, L., Röcke, C., & Martin, M. (2015, September). *Impact of cognition, personality, affect, and everyday life context on working memory training in older adults.* Poster presented at the URPP Dynamics of Healthy Aging Site Visit, Zurich, Switzerland.

Guye, S.*, von Bastian, C. C., Bezzola, L. & Martin, M. (2015, May). *Impact of cognition, personality, and affect on working memory training in older adults.* Poster presented at the LIFE Spring Academy, Ann Arbor, United States.

Guye, S.*, von Bastian, C. C., Bezzola, L. & Martin, M. (2014, March). *Impact of cognition, personality, affect, and everyday life on working memory training and transfer effects in healthy, older adults.* Poster presented at the INAPIC Fall Workshop, Zurich, Switzerland.

Guye, S.*, Zimmermann, K., Eschen, A., Zöllig, J., Mérillat, S., Jäncke, L., & Martin, M. (2012; May). *Der Einfluss eines räumlichen Gedächtnistrainings auf kognitive Fähigkeiten und neuronale Strukturen im Alter.* Poster presented at the LizentiandInnen-, Masterstudierenden und Doktorierenden-Kongress (LiMaDoKo), Zurich, Switzerland.

MEDIA APPEARANCES

2018 *Gehirndoping: Wie wir schlauer werden,* SRF „Einstein"

2018 *Spielerisch das Gehirn trainieren*, Radio SRF 1 "Ratgeber"

2017 *Training führt nicht zu einer generellen Leistungssteigerung*, Swiss Bulletin for Memory Training

2017 *Der Alltag ist das beste Training*, Schweizer Illustrierte

PUBLIC OUTREACH

Guye, S. (2017). Can cognitive training really make us smarter? Blog post for the BOLD Blog of the Jacobs Foundation.

Guye, S. (2016). Wie wirksam ist kognitives Training. Newsletter article for the URPP „Dynamics of Healthy Aging" Newsletter.

Guye, S. & Giroud, N. (2015). University Research Priority Program Dynamics of Healthy Aging. Newsletter article for the LIFE Community (the International Max Planck Research School «The Life Course: Evolutionary and Ontogenetic Dynamics»)

PROFESSIONAL TRAINING

2016 Seminare abwechslungsreicher gestalten (1 day)
Balthasar Eugster, lic. Phil., University of Zurich, Switzerland

2016 Power analysis for multilevel modeling (1/2 days)
Dr. Peter Wilhelm, University of Fribourg, Switzerland

2016 Presentation coaching (2 days)
Prof. Dr. Anja Janoschka, Hochschule Luzern, Switzerland

2016 Ambulatory assessment (2 days)
Prof. Dr. Ulrich Ebner-Priemer, Karlsruhe Institute of Technology, Germany

2016 Advanced mixed models with R (3 days)
Prof. Dr. Bertolt Meyer, TU Chemnitz, Germany

2016 Conducting computer-based studies online & offline with tatool web (3 days)
Dr. Claudia von Bastian, University of Colorado Boulder, USA

2016 Analysing intensive longitudinal data (4 days)
Prof. Dr. Niall Bolger, Columbia University, USA
Dr. Jean-Philippe Laurenceau, University of Delaware, USA

2015 Static and dynamic models for the analysis of longitudinal data (1 day)
Prof. Dr. Manuel Völkle, Humboldt University Berlin, Germany

2015 Modern methods for the analysis of change (4 days)
Prof. Dr. Paolo Ghisletta, University of Geneva, Switzerland

2015 Longitudinal structural equation modeling (4 days)
Prof. Dr. Todd Little, Texas Tech University, USA

2015 Multilevel modeling with R: For beginners (3 days)
Prof. Dr. Bertolt Meyer, TU Chemnitz, Germany

2014 Writing research articles in psychology (5 days)
Simon Milligan, Language Center UZH and ETHZ, Switzerland

2014 Introduction to data mining (1/2 day)
Prof. Dr. Abraham Bernstein, University of Zurich, Switzerland

2014 Introduction to Python (2 days)
Dr. Franziskus Liem, University of Zurich, Switzerland

2014 Neuropsychological assessment battery training (1 day)
Mona A. Bornschlegl, University of Bremen, Germany

2014 Missing data analysis in psychology and the behavioural sciences (3 days)
Prof. Dr. Tenko Raykov, Michigan State University, USA

2014 Time- and self-management (2 days)
Dipl. Psych. Anne Maria Jansen, University of Zurich, Switzerland

2014 Introduction to structural equation modeling using Mplus (3 days)
Prof. Dr. Fridtjof Nussbeck, University of Bielefeld, Germany

2014 Statistical parametric mapping (SPM) for neuroimaging (4 days)
Translational Neuromodeling Unit ETHZ and UZH, Switzerland

TEACHING EXPERIENCE

Spring 2017 Master seminar “Concepts and theories of cognitive development across the lifespan” in English, Department of Psychology, University of Zurich, Switzerland

Spring 2016 Master seminar “Quantitative research methods: Applied data analysis” in German & English, Hochschule Luzern (HSLU), Switzerland

Autumn 2014	Master seminar “Fitness fürs Gehirn [Fitness for the brain]” in German, Department of Psychology, University of Zurich, Switzerland
Autumn 2014	Bachelor seminar “Interactive introductory seminar course” in German, Department of Psychology, University of Zurich, Switzerland
Autumn 2013	Bachelor seminar “Interactive introductory seminar course” in German, Department of Psychology, University of Zurich, Switzerland
Spring 2013	Bachelor seminar “Practical course in experimental psychology” in German, Department of Psychology, University of Zurich, Switzerland
Spring 2012	Bachelor seminar “Psychological methods – An Introduction to SPSS” in German, Department of Psychology, University of Zurich, Switzerland

STUDENT SUPERVISION

Master thesis	Daniela Schwager (2015 – 2016)
Assistants	Aline Gaillard (2015), Enrico Capelli (2015), Simone Lerch (2016), Mirjam Imfeld (2016)
Interns	Michel Wälti (2014), Sabrina Müller (2014), Enrico Capelli (2014 – 2015), Annia Rüesch Ranganadan (2015)

OTHER CONTRIBUTIONS TO SCIENCES

Reviewer	Cochrane Reviews; Journal of Cognitive Enhancement; Rejuvenation Research; The Journal of Gerontology
2017 –	Editor of the URPP “Dynamics of Healthy Aging” bi-annual Newsletter
2016 – 18	Member of the peer mentoring group “Real life health measurement”
2014	Member of the peer mentoring group “Applied programming for psychologists”
2015 – 16	LIFE fellow speaker
MRI	Certified MRI user, Psychiatric University Hospital (PUK), Zurich, Switzerland